Experimental Investigations on Machining of CFRP Composites: Study of Parametric Influence and Machining Performance Optimization

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CERTIFICATE OF APPROVAL

Certified that the dissertation entitled **EXPERIMENTAL INVESTIGATIONS ON MACHINING OF CFRP COMPOSITES: STUDY OF PARAMETRIC INFLUENCE AND MACHINING PERFORMANCE OPTIMIZATION** submitted by **Kumar Abhishek** has been carried out under my supervision in fulfillment of the requirement for the award of the degree of ***Doctor of Philosophy*** in ***Mechanical Engineering*** at **National Institute of Technology**, **Rourkela**, and this work has not been submitted to any university/institute before for any academic degree/diploma.

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KUMAR ABHISHEK

Abstract

Carbon Fiber Reinforced Polymer (CFRP) composites are characterized by their excellent mechanical properties (high specific strength and stiffness, light weight, high damping capacity etc.) as compared to conventional metals, which results in their increased utilization especially for aircraft and aerospace applications, automotive, defense as well as sporting industries. With increasing applications of CFRP composites, determining economical techniques of production is very important. However, as compared to conventional metals, machining behavior of composites is somewhat different. This is mainly because these materials behave extremely abrasive during machining operations. Machining of CFRP appears difficult due to their material discontinuity, inhomogeneity and anisotropic nature. Moreover, the machining behavior of composites largely depends on the fiber form, the fiber content, fiber orientations of composites and the variability of matrix material. Difficulties are faced during machining of composites due to occurrence of various modes of damages like fiber breakage, matrix cracking, fiber–matrix debonding and delamination. Hence, adequate knowledge and in-depth understanding of the process behavior is indeed necessary to identify the most favorable machining environment in view of various requirements of process performance yields.

In this context, present work attempts to investigate aspects of machining performance optimization during machining (turning and drilling) of CFRP composites. In case of turning experiments, the following parameters viz. cutting force, Material Removal Rate (MRR), roughness average (R_a) and maximum tool-tip temperature generated during machining have been considered as process output responses. In case of drilling, the following process performance features viz. load (thrust), torque, roughness average (of the drilled hole) and delamination factor (entry and exit both) have been considered. Attempt has been made to determine the optimal machining parameters setting that can simultaneously satisfy aforesaid response features up to the desired extent. Using Fuzzy Inference System (FIS), multiple response features have been aggregated to obtain an equivalent single performance index called Multi-Performance Characteristic Index (MPCI). A nonlinear regression model has been established in which MPCI has been represented as a function of the machining parameters under consideration. The aforesaid regression model has been considered as the fitness function, and finally optimized by evolutionary algorithms like Harmony Search (HS), Teaching-Learning

Based Optimization (TLBO), and Imperialist Competitive Algorithm (ICA) etc. However, the limitation of these algorithms is that they assume a continuous search within parametric domain. These algorithms can give global optima; but the predicted optimal setting may not be possible to adjust in the machine/setup. Since, in most of the machines/setups, provision is given only to adjust factors (process input parameters) at some discrete levels. On the contrary, Taguchi method is based on discrete search philosophy in which predicted optimal setting can easily be achieved in reality. However, Taguchi method fails to solve multi-response optimization problems. Another important aspect that comes into picture while dealing with multi-response optimization problems is the existence of response correlation. Existing Taguchi based integrated optimization approaches (grey-Taguchi, utility-Taguchi, desirability function based Taguchi, TOPSIS, MOORA etc.) may provide erroneous outcome unless response correlation is eliminated. To get rid of that, the present work proposes a PCA-Fuzzy-Taguchi integrated optimization approach for correlated multi-response optimization in the context of machining CFRP composites. Application potential of aforementioned approach has been compared over various evolutionary algorithms.

Keywords: Carbon Fiber Reinforced Polymer (CFRP); Fuzzy Inference System (FIS); Multi-Performance Characteristic Index (MPCI); nonlinear regression; Harmony Search (HS); Teaching-Learning Based Optimization (TLBO); Imperialist Competitive Algorithm (ICA); Taguchi method; PCA-Fuzzy-Taguchi

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CHAPTER 1

BACKGROUND AND RATIONALE

1.1 Introduction

Carbon fiber reinforced polymer (CFRP) composites may be defined as fiber reinforced composite material that utilizes carbon fiber as the primary structural component (reinforcement) and thermosetting resins such as epoxy, polyester, or vinyl ester as matrix. In recent years, CFRP composites are becoming quite popular in the manufacturing industries especially in aerospace and automobile industries due to their excellent mechanical and thermal properties including high mechanical strength and low weight, good fatigue resistance, good corrosion and weather resistance, very low coefficient of thermal expansion and high strength-to-weight ratio. With the increased demand of CFRP composites in aforementioned industries, manufacturers are emphasizing more to study the machinability aspects of these composites. In general CFRP products are made to near-net-shape; however, machining is often carried out in order to remove excess material to meet dimensional accuracy and tolerance. But machining of these composites is somewhat different from machining of conventional metals; it is quite difficult due to their material discontinuity, anisotropic and inhomogeneous nature. There are several challenges with machining CFRP material:

- The fibers are characterized by high strength, which makes the material difficult to cut, leading to: wear on the cutting tool and splintering/fraying.
- It has a high elastic modulus, making it abrasive.
- The plastic matrix is sensitive to heat and can melt.
- The structure is built up by layers of material, which can lead to delamination.

The major drawbacks associated in machining of these composites are fiber pull out, breakage of fibers, delamination, matrix burning, matrix cracking and subsurface damage which lead to poor surface quality and dimensional inaccuracy. Hence, it becomes indeed essential for the manufacturer to understand machining behavior of CFRP composites. Out of several conventional machining operations, turning and drilling operations are commonly performed for machining of CFRP composites to make/assemble desired shape and size of product and to achieve required level of dimensional accuracy.

Earlier trend was to select the machining variables randomly based on the operator's skills in which product quality might not be as per the desired level. With advancement of time, manufacturers are giving more attention to enhance both quality and productivity, simultaneously. As machining parameters significantly influence on machining performance features, appropriate setting and proper control of machining parameters is of utmost importance to achieve desired product quality and satisfactory process performance (productivity). Hence, it is of vital necessity to go for optimization of machining parameters towards enhancing overall machining performance.

1.2 State of Art

The following section elaborates the outcome of the past research as documented in literature resource on machining and machinability aspects of Fiber Reinforced Polymer (FRP) composites.

Komanduri (1997) explained various issues involved in machining (conventional and nonconventional) of fiber reinforced composites. Mathew et al. (1999) experimentally investigated the effect of the geometry of a trepanning tool on thrust and torque during drilling of uni-directional glass fiber-reinforced plastic (UD-GFRP) laminates. The investigations revealed that the performance of the trepanning tool was found superior to that of conventional twist drills in terms of thrust, torque and hole quality. Low production cost and ease of regrinding were understood as its major additional advantages due to its simple geometry.

Davim et al. (2004) investigated on evaluating the cutting parameters (cutting velocity and feed rate) related to machining force in the work piece, delamination factor, surface roughness and international dimensional precision in two GFRP composite materials (Viapal VUP 9731 and ATLAC 382-05). A plan of experiments, based on an orthogonal array, was established considering milling with prefixed cutting parameters. An analysis of variance (ANOVA) was preformed to investigate the cutting characteristics of GFRP composite materials using cemented carbide (K10) end mill. Mohan et al. (2005) outlined the Taguchi optimization methodology applied to optimize cutting parameters in drilling of glass fiber reinforced composite (GFRC) material. ANOVA was used to study the effect of process parameters on machining process. The drilling parameters and specimen parameters evaluated were speed, feed rate, drill size and specimen thickness. Experiments were conducted using TRIAC VMC CNC machining center to relate the cutting parameters and material parameters on the cutting thrust and torque. An orthogonal array, Signal-to-Noise (S/N) ratio were employed to analyze the influence of these parameters on cutting force and torque during drilling. From the analysis of the Taguchi method indicated that among the all-significant parameters, speed and drill size were found imposing more significant influence on cutting thrust than the specimen thickness and the feed rate. Study of response table indicated that the specimen thickness, and drill size were the significant parameters in influencing the torque. From the interaction among process parameters, thickness and drill size together was found more dominant factor than any other combination for the torque characteristics.

Palanikumar et al. (2006) discussed the application of the Taguchi method with fuzzy logic to optimize the machining parameters for machining of GFRP composites with multiple characteristics. A multi-response performance index (MRPI) was introduced for optimization. The machining parameters viz., work piece (fiber orientation), cutting speed, feed rate, depth of cut and machining time were optimized with consideration of multiple performance characteristics viz., metal removal rate, tool wear, and surface roughness.

Palanikumar and Davim (2007) developed a mathematical model in order to predict the tool wear on the machining of GFRP composites using regression analysis and ANOVA to study the main and interaction effects of machining parameters, viz., cutting speed, feed rate, depth of cut and work piece fiber orientation angle. The adequacy of the developed model was verified by using coefficient of determination and residual analysis. This model could be effectively used to predict the tool wear on machining GFRP components within the ranges of variables studied. The influences of different parameters in machining GFRP composite were also analyzed in detail. Rubio et al. (2008) employed High Speed Machining (HSM) to realize high performance drilling of glass fiber reinforced plastics with reduced damage. A comparison between the conventional (F_d) and adjusted (F_{da}) delamination factor was presented. The experimental results indicated that the use of HSM was found suitable for drilling GFRP ensuring low damage levels.

Palanikumar et al. (2009) focused on the multiple performance optimizations on machining characteristics of glass fiber reinforced plastic (GFRP) composites. The cutting parameters used for the experiments, which were carried out according to Taguchi's L_{27}, 3-level orthogonal array, were cutting speed, feed and depth of cut. Statistical models based on second order polynomial equations were developed for the different responses. The Non-dominated Sorting Genetic Algorithm (NSGA-II) tool was used to optimize the cutting conditions, yielding a non-dominated solution set. Sait et al. (2009) presented desirability function analysis for optimizing the machining parameters on turning glass-fiber reinforced plastic pipes. In this work, based on Taguchi's L_{18} orthogonal array, turning experiments were conducted for filament wound and hand layup GFRP pipes using K20 grade cemented carbide cutting tool. The machining parameters such as cutting velocity, feed rate and depth of cut were optimized by multi-response considerations namely surface roughness, flank wear, crater wear and machining force. A composite desirability value was obtained for the multi-responses using individual desirability values from the desirability function analysis. Based on composite desirability value, the optimum levels of parameters were identified; significant contribution of parameters was also determined by analysis of variance.

Kilickap (2010) investigated the influence of the cutting parameters, such as cutting speed and feed rate, and point angle on delamination produced during drilling a GFRP composite. The damage generated associated with drilling GFRP composites were observed, both at the entrance and the exit during drilling. It was felt essential to obtain optimum cutting parameters minimizing delamination whilst drilling of GFRP composites. Moreover, this paper presented the application of Taguchi method and ANOVA for minimization of delamination influenced by drilling parameters and drill point angle. The optimum drilling parameter combination was obtained by using the analysis of Signal-to-Noise (S/N) ratio. The conclusion revealed that feed rate and cutting speed were the most influential factor on the delamination, respectively. The best results of the delamination were obtained at lower cutting speeds and feed rates. Mohan et al. (2010) examined optimization of drilling conditions of glass fiber reinforced plastic composite material using Genetic Algorithm (GA). In this work, the constrained optimization of cutting conditions was determined and treated by the application of genetic algorithm to determine the optimum values of cutting speed and feed rate which yielded minimum cost of drilling operation performed on a TRIAC VMC CNC machine. The results indicated that the model could effectively be used for predicting the machining conditions yielding the minimum cost of operation; the results were also compared with the optimization results obtained using geometric programming.

Palanikumar (2011) presented an approach for the optimization of drilling parameters with multiple performance characteristics based on the Taguchi's method with grey relational analysis. Taguchi's L_{16}, 4-level orthogonal array was used for the experimentation. The drilling parameters such as spindle speed and feed rate were optimized with consideration of multiple performance characteristics, such as thrust force, work piece surface roughness and delamination factor. The analysis of grey relational grade indicated that feed rate was the most influential parameter than spindle speed. Khan and Kumar (2011) dealt with the machining of glass fiber reinforced plastic composite material. GFRP composite material was fabricated using E-glass fiber with unsaturated polyester resin through a filament winding process. Machining studies were carried out using two different alumina cutting tools: namely, a Ti[C, N] mixed alumina cutting tool (CC650) and a SiC whisker reinforced alumina cutting tool (CC670). The machining process was performed at different cutting speeds at constant feed rate and depth of cut. The performance of the alumina cutting tools was evaluated by measuring the flank wear and surface roughness of the machined GFRP composite material. Attempt was also made to analyze the main wear mechanism of alumina cutting tools while machining GFRP composite material.

Latha et al. (2011) carried out drilling tests on computer numeric control (CNC) drilling machine. The parameters considered for the drilling investigations were spindle speed, feed rate and diameter of the drill bits. Multiple regression analysis was used for the modelling of process parameters in drilling of GFRP composites. Taguchi's S/N ratio analysis and desirability based approach were used for the optimization of process parameters for studying the delamination in drilling of GFRP composites. The results revealed that the factor feed rate and drill diameter were the most influential parameters which affected the delamination in drilling of GFRP composites. The interaction between the parameters also affected the delamination in drilling of GFRP composites. Hussain et al. (2011) dealt with the study of machinability of GFRP composite tubes of different fiber orientation angle varying from 30^0 to 90^0. Machining studies were carried out on an all geared lathe using three different cutting tools: namely Carbide (K-20), Cubic Boron Nitride (CBN) and Poly-Crystalline Diamond (PCD). Experiments were conducted based on the established Taguchi's Design of Experiments (DOE) L_{25} orthogonal array on an all geared lathe. The cutting parameters considered were cutting speed, feed, depth of cut, and work piece (fiber orientation). The performances of the cutting tools were evaluated by measuring surface roughness (R_a) and Cutting force (F_z). A second order mathematical model in terms of cutting parameters was developed using Response Surface Methodology (RSM). The results indicated that the developed model was suitable for prediction of surface roughness and cutting force in machining of GFRP composites.

Gupta and Gill (2012) dealt with the study and development of a cutting force prediction model for the machining of unidirectional glass fiber reinforced plastics (UD-GFRP) composite using regression modelling and optimization by simulated annealing. The process parameters considered here included cutting speed, feed rate and depth of cut. The predicted values of the radial cutting force model were compared with the experimental values. The results of prediction were quite close with the experimental values. The influences of different parameters in machining of UD-GFRP composite were also analyzed.

Kumar et al. (2012) conducted a study on machining of unidirectional glass fiber reinforced plastic (UD-GFRP) composite material to investigate the effect of tool nose radius, tool rake angle, feed rate, cutting speed, depth of cut and along with cutting environment (dry, wet and cooled (5-7℃) temperature) on the surface roughnes s produced. The experimental results revealed that the most significant machining parameters for surface roughness was feed rate followed by cutting speed. Cutting environment did not influence the surface roughness significantly. Panneerselvam et al. (2012) used Grey Relational Analysis (GRA) approach for study and optimization of the machining parameters (Tool condition (TC), number of flutes (z), cutting speed (V) and feed rate (f)) on milling of GFRP in order to minimize surface delamination, machining forces, cutting torque and surface roughness. For this study; GFRP was fabricated by hand layup with 33% fiber and 66% general purpose resin. Experiments were designed and carried out as per orthogonal array and parameters were optimized using Grey Relational Grade (GRG). Rajamurugan et al. (2012) established an empirical relationship between the thrust force and drilling parameters (tool rotational speed, tool feed rate, drill diameter and fiber orientation angle) in drilling of GFRP Composites. Statistical tools such as design of experiments, analysis of variance, and regression analysis were explored to develop the relationships. The developed empirical relationship could be effectively used to predict the thrust force of drilled holes at the 99% confidence level.

Balamugundan et al. (2012) attempted multi-characteristics optimization during milling of friction stir processed glass fiber reinforced plastic composites. In this study, GFRP plates were friction stir processed (FSP) to enhance their microstructural properties. The friction stir processed plates were then subjected to milling with solid carbide K6 end mill tool. Taguchi's L_9 orthogonal array was used for the experimental design. The milling process parameters such as spindle speed, feed and depth of cut were optimized with multiple performance considerations of surface roughness and delamination. Multi-objective optimization of machining parameters was done through desirability function analysis. The optimum machining parameters were identified by a composite desirability value obtained from desirability function analysis. The performance index and significant contribution of process parameters were determined by ANOVA.

Erkan et al. (2013) reported a study in which a GFRP composite material was milled to minimize the damages on the machined surfaces, using two, three and four flute end mills at different combinations of cutting parameters. Experimental results showed that the damage factor increased with increasing cutting speed and feed rate; on the other hand, it was found that the damage factor decreased with increasing depth of cut and number of the flutes. In addition, ANOVA results revealed that the feed rate was the most influential parameter affecting the damage factor in end milling of GFRP composites. Also, Artificial Neural Network (ANN) models with five learning algorithms were used in predicting the damage factor to reduce number of expensive and time-consuming experiments. ANN was notably found successful in predicting the damage factor.

Parida (2012) examined the surface roughness of glass fiber reinforced plastic composite on the basis of cutting parameters such as speed, feed rate and depth of cut. The surface quality was found to relate closely to the cutting speed, feed rate, and depth of cut. The Taguchi method was adopted in this study to investigate the influence of surface roughness by cutting parameters. Further, ANOVA was used to analyze the influence of process parameters and their interaction effects during machining. Rajamurugan et al. (2013) developed empirical relationships between the drilling parameters such as fiber orientation angle, tool feed rate, rotational speed and tool diameter with respect to delamination in drilling of GFR–polyester composites. The empirical relationship was developed by using RSM. The result indicated that the increase in feed rate and drill diameter increased the delamination size; whereas, there was no clear effect observed for fiber orientation angle. The spindle speed showed only little effect on delamination in drilling of GFR–Polyester composites.

Sreenivasulu (2013) focused on the influence of cutting speed, feed rate and depth of cut on the delamination damage and surface roughness on glass fiber reinforced polymeric composite material during end milling. Taguchi design method was employed to investigate the machining characteristics of GFRP. From the results of ANOVA, it was concluded that cutting speed and depth of cut were the most significant factors affecting the responses. Finally, artificial neural network was applied to compare the predicted values with the experimental values, the deviations were found acceptable; it showed good agreement between the predictive model results and the experimental measurements.

Mehbudi et al. (2013) applied ultrasonic assisted drilling to reduce thrust force in drilling of GFRP laminates. In order to conduct experiments, a setup was designed and fabricated to apply both vibrations and rotation to drill bits. Using Taguchi method, a set of experiments was conducted with feed rate, spindle speed, and ultrasonic vibration amplitude as control factors. The results showed that applying ultrasonic vibration could reduce the thrust force and, therefore, the drilling induced delamination dramatically. Ramesh et al. (2013) studied the hole quality in drilling thick non-laminated GFRP composite rods using coated tungsten carbide twist drill. The GFRP composite rods were made by pultrusion method with high fiber weight fraction. Taguchi's orthogonal array and ANOVA were employed to study the influence of process parameters such as feed and spindle speed on ovality (hole diameter inaccuracy) of the drilled holes. The optimum level of process parameters towards minimum ovality was obtained to achieve defect controlled drilling of pultruded GFRP composite rods. The influence of speed on ovality was found insignificant. The influence of feed was found significant on ovality of the drilled holes. It was found that the influence of process parameters on hole quality in non-laminated composite rods differed with drill geometry and also differed from the influence of process parameters on hole quality in laminated composites.

Ali et al. (2013) assessed the influence of drilling and milling parameters on hole making process of woven laminated GFRP material. A statistical approach was used to understand the effects of the control parameters on the response variables. Analysis of variance was performed to isolate the effects of the parameters affecting the hole making in the two types of cutting processes. The results showed that milling process was more suitable than drilling process at high level of cutting speed and low level of feed rate, when the cutting quality (minimum surface roughness, minimum difference between upper and lower diameter) was of critical importance in the manufacturing industry, especially for precision assembly operation. Jenarthanan and Jeyapaul (2013) presented an approach for optimizing the machining parameters on milling glass fiber reinforced plastic composites. Optimization of machining parameters was done by desirability function analysis (DFA). In this work, based on Taguchi's L_{27} orthogonal array, milling experiments were conducted for GFRP composite plates using solid carbide end mills with different helix angles. The machining parameters such as, spindle speed, feed rate, helix angle and fiber orientation angle were optimized by multi-response considerations namely surface roughness, delamination factor and machining force. Gill et al. (2013) conducted experimental investigations to determine the effects of cutting conditions and tool geometry on the cutting forces in turning of unidirectional glass fiber reinforced plastics (UD-GFRP) composites. In this experimental study, carbide tool (K10) having different tool nose radius and tool rake angle was used. Experiments were conducted based on Taguchi's technique L_{18} orthogonal array on a lathe machine. It was found that the depth of cut was the cutting parameter, which had greater influence on cutting forces. The effect of the tool nose radius and tool rake angles on the cutting forces were also found considerably significant. Based on statistical analysis, multiple regression model for cutting forces was also derived.

Kumar et al. (2013) presented a utility concept for multi-response optimization in turning uni-directional glass fiber-reinforced plastics composite using Carbide (K10) cutting tool. The Taguchi method (Orthogonal L_{18} array) was employed in the experimental work. The process parameters selected for this study were tool nose radius, tool rake angle, feed rate, cutting speed, depth of cut, and cutting environment. Statistically significant parameters were found to simultaneously minimize surface roughness and maximize the material removal rate by ANOVA. Babu and Sunny (2013) presented delamination study of composite materials by conducting drilling experiments using Taguchi's L_{25}, 5-level orthogonal array; ANOVA was used to analyze the data obtained from the experiments and finally determine the optimal drilling parameters in drilling GFRP composite materials. Experiments were also conducted to determine whether varying feed and spindle speed during drilling could reduce the delamination.

Ramesh et al. (2013) reported an investigation on a non-laminated glass fiber reinforced plastic composite manufactured by pultrusion process which was drilled with a coated cemented carbide drill. Taguchi's orthogonal array and ANOVA were employed to study the influence of process parameters such as feed and spindle speed on thrust force, torque and damage factor. The optimum level of process parameters towards minimum thrust force, minimum torque and lower damage factor were obtained to achieve defect controlled drilling of GFRP composites. Correlations for thrust force, torque and damage factor with process parameters were also established. Among the process parameters examined, feed significantly influenced both the thrust force and torque; whereas, the influence of spindle speed on the above was relatively insignificant. The influence of feed and spindle speed on damage factor at both entrance and exit of the work piece was found insignificant.

Vankanti and Ganta (2014) optimized process parameters namely, cutting speed, feed, point angle and chisel edge width in drilling of glass fiber reinforced polymer composites. In this work, experiments were carried out as per the Taguchi's L_9 orthogonal array to study the influence of various combinations of process parameters on hole quality. ANOVA test was conducted to determine the significance of each process parameter on drilling. The results indicated that feed rate was the most significant factor influencing the thrust force followed by speed, chisel edge width and point angle; cutting speed was the most significant factor affecting the torque, speed and the circularity of the hole followed by feed, chisel edge width and point angle. This work was found useful in selecting optimum values of various process parameters that would not only minimize the thrust force and torque but also reduce the delimitation and improve the quality of the drilled hole. Khan et al. (2012) developed two different evolutionary algorithm-based neural network models to optimize the unit production cost during machining of GFRPs. The hybrid neural network models were, namely, genetic algorithm based neural network (GA-NN) model and particle swarm optimization based neural network (PSO-NN) model. These hybrid neural network models were used to find the optimal cutting conditions of Ti[C,N] mixed alumina-based ceramic cutting tool (CC650) and SiC whisker-reinforced alumina based ceramic cutting tool (CC670) on machining glass fiber-reinforced plastic (GFRP) composite. An orthogonal design and ANOVA was employed to determine the effective cutting parameters on the tool life. The GA-NN and PSO-NN models were compared for their performance. Optimal cutting conditions obtained with the PSO-NN model were the best possible compromise compared with the GA-NN model during machining GFRP composite using alumina cutting tool. This model also proved that neural networks were capable of reducing uncertainties related to the optimization and estimation of unit production cost.

Hussain et al. (2014) used fuzzy logic combined with Taguchi method for the optimization of multiple performance characteristics considering surface roughness, cutting force, specific cutting pressure and cutting power during machining of GFRP composites. Experiments were planned using Taguchi's L_{25} orthogonal array with the cutting conditions prefixed. The process parameters considered were work piece (fiber orientation), cutting speed, feed and depth of cut. The machining tests were performed on a lathe using carbide (K20) cutting tool. The results indicated that the optimization technique was greatly helpful in optimizing the multiple performance characteristics simultaneously in machining of GFRP composites. Shunmugesh et al. (2014) reported an experimental investigation on drilling of GFRPs in which L_{27} orthogonal array was used for determining delamination as well as surface roughness. The process parameters like spindle speed, tool point angle and feed rate were combined to know the optimal parameters. Grey Relational Analysis (GRA) was performed to observe the effect of parameters and its interaction. Experiment results revealed that spindle speed was found as the most significant factor while point angle contributed to the least.

Aspects of GFRP composite machining have been highlighted in aforesaid sections. The following sections illustrate in-depth understanding of past research on machining of CFRP composites.

Koplev et al. (1983) examined the cutting of unidirectional CFRP, perpendicular as well as parallel to the fiber orientation. The authors discussed the formation of the chips, and the quality of the machined surface. The cutting forces parallel and perpendicular to the cutting direction were measured for various parameters. The results correlated to the formation of chips and the wear of the tool. Kim et al. (1992) experimentally investigated the machinability of high-strength carbon fiber epoxy composite materials in turning operations. The chip formation mechanisms and the Taylor tool-wear constants were determined and the surface roughness was measured with respect to cutting speeds and feeds. Santhanakrishnan et al. (1992) performed face-turning trials on carbon-fiber-reinforced plastics (CFRP) using sintered carbides (P30 and K20). The cutting forces were measured using a piezo-electric type dynamometer. The worn-out tool edges, the machined CFRP surfaces and the chips were examined under the scanning electron microscope. The force measurements revealed the existence of a critical velocity for each tool during machining. The machined CFRP surface had a more uniform surface texture with insignificant fiber pull-out.

Lin and Chen (1996) studied the effects of increasing cutting speed on drilling characteristics of carbon fiber-reinforced composite materials. The effects of increasing cutting speed on average thrust force, torque, tool wear and hole quality for both multi-facet drill and twist drill were studied. It was found that increasing cutting speed would accelerate tool wear. The thrust force increased as drill wear increased. Although tool geometries changed quickly due to the fast development of tool wear and the thrust force increased drastically as cutting speed increased, an acceptable hole entry and exit quality could be maintained. It was concluded that tool wear was the major problem encountered when drilling carbon fiber reinforced composite materials at high speed. Chen (1997) proposed the concept of delamination factor (i.e. the ratio of the maximum diameter D_{max} in the damage zone to the hole diameter D) in order to analyze and compare easily the delamination degree in drilling of carbon fiber-reinforced plastic composite laminates. Experiments were performed to investigate the variations of cutting forces with or without onset of delamination during the drilling operations. The effects of tool geometry and drilling parameters on cutting force variations in CFRP composite materials drilling were also experimentally examined. The experimental results showed that the delamination-free drilling processes could be obtained by the proper selections of tool geometry and drilling parameters. The effects of drilling parameters and tool wear on delamination factor were also discussed. An experimental investigation of flank surface temperatures was also presented in this paper. Experimental results indicated that the flank surface temperatures increased with increasing cutting speed but decreasing feed rate. Optimal cutting conditions were proposed to avoid damage from burning during the drilling processes. Rahman et al. (1999) developed feasible techniques for machining of carbon fiber reinforced composites. Fundamental studies on the machining of CFRP were carried out, where the machining parameters namely cutting speed, feed rate and depth of cut, were varied. Three types of cutting tool inserts namely, uncoated tungsten carbides, ceramic and cubic boron nitride (CBN), were used to machine two types of specimens, short (discontinuous) and long (continuous) fiber carbon epoxy composites. For short carbon fiber composites, experimental data showed that the tool wear, the surface finish and the cutting force fluctuated with respect to the depth of cut, the feed rate and the cutting speed. However, for long fiber carbon composites, for a fixed material removal rate, the tool wear was found minimum when the CFRP composites were machined at lower cutting speeds. In addition, CBN inserts showed superior tool wear properties and better surface finish as compared to tungsten carbide and ceramic inserts.

Ferreira et al. (1999) reported practical experiments in turning, to study the performance of different tool materials such as ceramics, cemented carbide, cubic boron nitride (CBN), and diamond (PCD). The results showed that only diamond tools were found suitable for use in finish turning. Mathew et al. (1999) reported that carbon fiber reinforced plastic (CFRP) composites were found to be cut satisfactorily by a pulsed Nd: YAG laser at the optimum process parameter ranges. Predictive models were developed based on important process parameters, viz. cutting speed, pulse energy, pulse duration, pulse repetition rate and gas pressure. The responses considered were the heat-affected zone (HAZ) and the taper of the cut surface. The optimization of process parameters was carried out using Response Surface Methodology (RSM). The thermal properties of the constituent material and the volume fraction of the fibers were the principal factors controlling the cutting performance. The effect of the process parameters on the output responses was also discussed.

Enemuoh et al. (2001) presented a comprehensive approach to select cutting parameters for damage-free drilling in carbon fiber reinforced epoxy composite material. The approach was based on a combination of Taguchi's experimental analysis technique and a multi-objective optimization criterion. The optimization objective included the contributing effects of the drilling performance measures: delamination, damage width, surface roughness, and drilling thrust force. A hybrid process model based on a database of experimental results together with numerical methods for data interpolation were used to relate drilling parameters to the drilling performance measures. Case studies were presented to demonstrate the application of this method in the determination of optimum drilling conditions for damage-free drilling in BMS 8-256 composite laminate. A process map based on the results was presented as a tool for drilling process design and optimization for the investigated tool/material combination. Davim and Reis (2003) presented an approach to select cutting parameters for damage-free drilling in carbon fiber reinforced epoxy composite material. The approach was based on a combination of Taguchi's techniques and on the ANOVA. A plan of experiments, based on the techniques of Taguchi, was performed drilling with cutting parameters prefixed in an autoclave carbon fiber reinforced plastic laminate. The ANOVA was employed to investigate the cutting characteristics of CFRPs using High Speed Steel (HSS) and Cemented Carbide (K10) drills. The objective was to establish a correlation between cutting velocity and feed rate with the delamination in a CFRP laminate. The correlation was obtained by multiple linear regressions. Finally, confirmation tests were performed to make a comparison between the results foreseen from the mentioned correlation. Hu and Zhang (2004) investigated the grinding performance of epoxy matrix composites reinforced by unidirectional carbon fibers, using an alumina grinding wheel. Emphasis was placed on understanding the effect of fiber orientations and grinding depths on the grinding force and surface integrity, and on understanding the grinding mechanisms, with a comparison to orthogonal cutting. It was found that greater grinding forces occurred at a fiber orientation between 60◦ and 90◦, but poorer grinding surface finish took place between 120◦ and

180◦. The surface integrity was highly dependent on the fiber orientation and the depth of grinding, which was very similar to the results of orthogonal cutting.

Davim and Reis (2005) presented a study that evaluated the cutting parameters (cutting velocity and feed rate) under the surface roughness, and damage in milling laminate plates of carbon fiber reinforced plastics (CFRPs). A plan of experiments, based on the Taguchi's method, was established considering milling with prefixed cutting parameters in an autoclave CFRP composite material. ANOVA was performed to investigate the cutting characteristics of CFRP composite material using cemented carbide (K10) end mills. The authors attempted to establish a model using multiple regression analysis between cutting velocity and feed rate with the surface roughness and damage in a CFRP composite material. Gaitonde et al. (2008) presented the effects of process parameters on delamination during high-speed drilling of carbon fiber reinforced plastic composites. The damage caused at the entrance of the drilled hole was characterized by delamination factor, which was evaluated by considering cutting speed, feed rate and point angle as affecting process parameters. The drilling experiments using cemented carbide (K20) twist drills were performed based on full factorial design of experiments with three levels defined for each of the process parameters. The computed values of delamination factor were empirically related to process parameters by developing a second order non-linear regression model based on response surface methodology. The effects of cutting speed, feed rate and point angle on delamination factor were analyzed using the models by generating response surface plots. The investigations revealed that the delamination tendency decreased with increase in cutting speed. The study also suggested low values of feed rate and point angle combination for reducing the damage. The details of model development and model adequacy test by ANOVA were presented in this paper.

Faraz et al. (2009) offered an approach in unveiling and introducing the cutting edge rounding (CER) (a latent wear characteristic as a measure of sharpness/bluntness) of uncoated cemented carbide tools during drilling CFRP composite laminates. Rawat and Attia (2009) presented an experimental investigation of the wear mechanisms of tungsten carbide (WC) drills during dry high speed drilling of quasi-isotropic woven graphite fiber epoxy composites.

Iliescu et al. (2010) presented the prediction and evaluation of thrust force in drilling of carbon composite material. In order to extend tool life and improve quality of hole drilling, a better understanding of uncoated and coated tool behaviors was felt indeed required. This paper described the development of a phenomenological model between the thrust force, the drilling parameters and the tool wear. The experimental results indicated that the feed rate, the cutting speed and the tool wear were the most significant factors affecting the thrust force. The model could effectively be used for tool-wear monitoring. Tsao and Chiu (2011) developed an innovative device in order to solve the problems of relative motion and chip removal between the outer and inner drills in drilling CFRP composite laminates. In addition, this study investigated the influence of drilling parameters (cutting velocity ratio, feed rate, stretch, inner drill type and inner drill diameter) on thrust force of compound core-special drills.

Boudelier et al. (2011) proposed a methodology to optimize process parameters for trimming applications with diamond abrasive cutters. This methodology was based on the study of quality of trimmed surface, through material integrity and surface roughness, and on the study of cutting mechanisms. Results showed that diamond grits size must be chosen according to the required surface roughness. Feed rate must respect cutting limitations due to CFRP removal mechanisms with abrasive cutters, which were identified through analyses of specific cutting energy. Finally, a protocol in two steps was proposed to determine the optimum process parameters according to the application. Firstly, constraint functions due to respect of quality and to limiting cutting phenomena were defined. Thus, limiting values of process parameters were determined. Then, process parameters were selected in order to optimize productivity.

Hintze et al. (2011) investigated the occurrence of delamination of the top layers during the machining of CFRP tape, with the focus being on the process of contour milling. The occurrence and propagation of delamination were studied by milling slots in unidirectional CFRP specimens having different fiber orientations and mainly analyzing the slot tip. This allowed the key mechanisms to be clarified. The results showed that delamination was highly dependent on the fiber orientation and the tool sharpness. The experiments allowed derivation of a novel system for describing the occurrence and propagation of delamination during milling. Furthermore, the principles also apply for drilling. The results allowed customization of the machining procedure to reduce and in some cases totally avoid delamination, leading to a significant increase in the quality of components.

Rajasekaran et al. (2012) concentrated on the understanding of machining process in turning of carbon fiber reinforced polymeric composites using ceramic cutting tool. The experimentation was carried out using three machining parameters namely cutting speed, feed and depth of cut towards identification of machining parameters that played a dominant role on surface roughness. Further the study identified the combination of machining parameters that provided desirable surface roughness. It used Taguchi's orthogonal array for easy conduction of experimentation and analysis of variance for analyzing the machining parameters. It was observed that the ceramic cutting tool offered satisfactory level of surface roughness.

Krishnaraj et al. (2012) reported an experimental investigation of a full factorial design performed on thin CFRP laminates using K20 carbide drill by varying the drilling parameters such as spindle speed and feed rate to determine optimum cutting conditions. The hole quality parameters analyzed in this study included hole diameter, circularity, peel-up delamination and push-out delamination. ANOVA was carried out for hole quality parameters and their contribution rates were determined. Genetic Algorithm (GA) was used in the multiple objective optimization in order to find the optimum cutting conditions for defect free drilling. Tool life of the K20 carbide drill was predicted at optimized cutting speed and feed. Calzada et al. (2012) presented the development and implementation of a microstructure-based finite element model for the machining of carbon fiber-reinforced polymer composites. The model was capable of describing the fiber failure mode occurring throughout the chip formation process. Characteristic fiber length in the chips, and machining forces for microstructures with fibers orientated at 0◦, 45◦, 90◦, and 135◦ were examined. For model validation purposes, the model-based machining performance predictions were compared to the machining responses from a set of orthogonal machining experiments. A parametric study was presented that identified a robust tool geometry, which minimized the effects of fiber orientation and size on the machining forces.

Pecat et al. (2012) investigated a circumferential milling process of unidirectional CFRP. For this purpose the cutting parameters and conditions such like cutting speed, fiber orientation and work piece temperature were varied. The examination of cross-sectional micrographs showed that the damage mechanism as well as the depth of sub-surface damages was strongly dependent on the fiber orientation of the CRFP material. A significant reduction of sub-surface damages was observed for higher work piece temperatures which could provide a potential for higher process performance by maintaining the components integrity at the same time. Furthermore it was found that higher cutting speeds result in fiber bending in the sub-surface region of the milled surfaces. For lower work piece temperatures a crucial raise of cutting forces was found. Heisel and Pfeifroth (2012) presented the results of investigations concerning the influence of the point angle of a drill tool and increased cutting speeds on machining forces and drill hole quality (delamination, fraying, burr formation). Elevated point angles resulted in increased feed force while the drilling torque stayed almost constant. The assessment of characteristics concerning drill holes showed that the quality at the entrance was the best when using point angles > 180°, while it was poor at the exit. The increase in cutting speed lead to almost no differences in drill hole quality but lead to rising feed forces and decreasing drilling torques.

Isbilir and Ghassemieh (2012) developed a 3D finite element (FE) model of the drilling process in the carbon fiber reinforced composite. The FE model was used to investigate the effects of cutting speed and feed rate on thrust force, torque and delamination in the drilling of carbon fiber reinforced laminated composite. A mesoscale FE model taking into account of the different oriented plies and interfaces was proposed to predict different damage modes in the plies and delamination. For validation purposes, experimental drilling tests were performed and compared to the results of the finite element analysis. Krishnamoorthy et al. (2012) used Taguchi's L_{27} orthogonal array to perform drilling of CFRP composite plates. In order to improve the quality of the holes drilled, the optimal combination of drilling parameters was chosen using grey relational analysis. Grey fuzzy optimization of drilling parameters was based on five different output performance characteristics, namely, thrust force, torque, entry delamination, exit delamination and eccentricity of the holes. ANOVA was used to find the percentage contribution of the drilling parameters. It was found that feed rate was the most influential factor in drilling of CFRP composites.

Karpat and Polat (2013) developed a mechanistic force model for double helix tools based on CFRP milling force data obtained on flat end mills. The aforementioned model could be used to improve double helix tool designs and to optimize milling process parameters. Shahrajabian and Farahnakian (2013) presented a methodology for the determination of the optimal cutting parameters (spindle speed, feed rate and tool point angle) during drilling of carbon fiber reinforced polymer composites to maximize the material removal rate by considering surface roughness, delamination and thrust force as the constraints through coupling Response Surface Method (RSM) and Genetic Algorithm (GA).

Isbilir and Ghassemieh (2013) developed three-dimensional (3D) FE model for drilling CFRP. A 3D progressive intra-laminar failure model based on the Hashin's theory was considered. Also an inter-laminar delamination model which included the onset and growth of delamination by using cohesive contact zone was developed. The developed model with inclusion of the improved delamination model and real drill geometry was used to make comparison between the step drill of different stage ratio and twist drill. Thrust force, torque and work piece stress distributions were estimated to decrease by the use of step drill with high stage ratio. The model indicated that delamination and other work piece defects could be controlled by selection of suitable step drill geometry. Hence, the 3D model could be used as a design tool for drill geometry for minimization of delamination in CFRP drilling. Najem (2013) presented the effects of machining parameters on surface roughness during high-speed drilling of carbon fiber reinforced plastic composite. The machining experiments were carried out on lathe using two levels of factors. The factors considered were: % volume fraction of carbon fiber, cutting speed, drill diameter and feed rate. A procedure was developed to assess and optimize the chosen factors to attain minimum surface roughness by incorporating: (i) response table and effect graph, (ii) normal probability plot (iii) analysis of variance technique. It was observed that the technique used was convenient to predict the main effects and interaction effects of different influential combinations of machining parameters. Feed rate was the factor, which had greater influence on surface roughness followed by % volume fraction of fiber and drill diameter. The interaction between all parameters had more influence on surface roughness, followed by (drill diameter and feed rate) and (% volume fraction of fiber and drill diameter) comparing with other interactions on the machining of CFRP composites.

Khairusshima et al. (2013) studied the effect of chilled air on tool wear and work piece quality during milling of carbon fiber-reinforced plastic. The delamination factor of CFRP was also found to improve at higher cutting speeds during chilled-air machining. Yashiro et al. (2013) investigated on the cutting temperature when dealing with carbon fiber-reinforced plastics (CFRPs). Temperatures higher than the glass-transition temperature of the matrix resin were not favorable as they damage the CFRP. In this research, the cutting temperature in the end mill machining process was measured using three methods. The measured cutting point temperature exceeded the glass-transition temperature. However, the influence of temperature elevation at the cutting point could be reduced by taking a suitable distance from the machined surface depending on the cutting speed. In addition, observation of the machined surface with SEM revealed that the matrix resin at the machined surface was not damaged even if the cutting speed was over 300 m/min. This phenomenon depended on the low thermal conductivity of the CFRP. Therefore, high-speed cutting was recommended applicable for the milling of CFRP.

Sheikh-Ahmad and Mohammed (2014) conducted edge trimming of carbon fiber reinforced composites using diamond abrasive cutters and the effect of feed rate, spindle speed and depth of cut on machining quality was investigated. Cutting forces, specific cutting energy, surface roughness and work piece temperature were measured and analyzed. It was found that depth of cut was the most important parameter to influence machinability. Trimming with low equivalent chip thickness values was found to be the most suitable in terms of the level of machining responses and machining damage. The cutting temperatures were found to exceed the glass transition temperature of the epoxy matrix when machining with large depth of cut. Qin et al. (2014) studied delamination analysis of the helical milling of carbon fiber reinforced plastics. Based on full factorial experimental design, helical milling experiments were performed by using a special cutter. The correlation between the delamination and the process parameters was established by developing an artificial neural network (ANN) model. The effects of the process parameters on delamination at the exit of the machined holes were analyzed by using this model and the predicted results. The significance of the process parameters in the improvement of the hole quality in helical milling was also assessed in course of this study.

Ramirez et al. (2014) focused on the evaluation of tool wear and surface integrity in the context of CFRP cutting. Series of drilling experiments were performed on CFRP plates using cemented carbide solid drills to investigate correlations between tool damage, cutting forces, temperature and hole surface quality. The authors developed a methodology to measure the drilling temperature and to assess the quality of the hole surfaces where uncut fibers occurred. A discussion on the definition of the surface topography was also proposed for CFRP work material. Li et al. (2014) presented the experimental data relating to surface roughness (2D and 3D) and work piece integrity when drilling unidirectional CFRP laminates with varying lay-up configurations at different feed rates using diamond coated carbide tools. Voß et al. (2014) introduced an extensive study on CFRP chip roots for five different unidirectional fiber orientations using an orthogonal cutting test rig. Intentionally weakened work pieces were produced first. These work pieces enabled truly representative cutting conditions due to a continuous cut and constant but wide range adaptable cutting speeds. Analyses of the chip roots were based on light microscopy (i), scanning electron microscopy (SEM) (ii) and micrographs (iii). The results could be a great help to understand the wear mechanisms when machining CFRPs. As a result fracture orientations, adhering abrasion particles, chip formation and chip movement allowed for the understanding of CFRP chip formation.

Guu et al. (2001) investigated electrical discharge machining (EDM) of carbon fiber reinforced carbon composite material. The characteristics of composites machined by EDM were studied in terms of machining parameters. An empirical model of the composites was also proposed based on the experimental data. The composite material was produced by an electrical discharge sinker using a graphite electrode. The work piece surface and resolidified layers were examined by scanning electron microscopy (SEM). Moreover, surface roughness was determined with a surface profilometer. Experimental results indicated that the extent of delamination, thickness of the recast layer, and surface roughness were proportional to the power input. The EDM process effectively produced excellent surface characteristics and high quality holes in composites under low discharge energy conditions.

Habib (2014) studied electrical discharge machining (EDM) of carbon fiber reinforced plastic (CFRP) material. This paper attempted to develop an appropriate machining strategy for a maximum process criteria yield. A feed-forward back-propagation neural network model was developed to model the machining process. The three most important parameters-material removal rate, tool electrode wear rate and surface roughness-were considered as measures of the process performance. Experiments were carried out over a wide range of machining conditions to study the effect of input parameters on the machining performance. The experimental data was used for the training and verification of the model. Testing results demonstrated that the model was suitable for predicting the response parameters accurately as a function of most effective control parameters, i.e. pulse duration, peak current and tool electrode rotational speed.

1.3 Motivation and Objectives

Literature depicts that extensive effort has been made by previous researchers on understanding of machining as well as machinability aspects of FRP composites. Considerable amount of work has been carried out to investigate the machining process behavior like parametric influence, mechanism of chip formation, and various modes of damages of the work piece during machining. Effects of tool material and tool geometry have been studied on influencing various process performance features viz. MRR, roughness average, delamination factor, cutting force, extent of tool wear etc. Mathematical models have been established to represent the functional relationship of individual process output features with respect to various process inputs. However, it has been observed that as compared to CFRP composites, considerable volume of research has been carried out on machining of GFRP composites.

Owing to the growing worldwide application of CFRP composites over automotive, aerospace, defense and sport industries, quality machining of these composites has become a challenge. As compared to conventional metal, machining of FRP composites faces various problems due to matrix cracking, fiber pull-out, fiber breakage, delamination etc. Aforesaid damages may deteriorate quality of the machined part. Hence, selection of appropriate process variables is very important to reduce various machining induced damages, and thereby, to improve quality of the machined product resulting enhancement of overall process performance.

The challenge arises in engineering optimization problems when several conflicting responses (output parameters) simultaneously come into existence. The objective function may be multimodal (i.e. more than one local minimum or maximum); but the main aim is to evaluate the global optimal values within the given search domain. Classical/traditional methods (mathematical methods) of optimization are found insufficient to handle these types of problems because of their computational drawbacks (such as complex derivatives, sensitivity to initial values, and the large amount of enumeration memory required). Hence, advanced heuristic and metaheuristic optimization algorithms are advised which are based on simulations to solve optimization problems as they combine rules and randomness to mimic natural phenomena. These techniques can efficiently solve the optimization problems, whether the objective functions are stationary or non-stationary (time-dependent), linear or nonlinear, continuous or discontinuous to find solution near to global optimum in lesser time and with lesser computational effort.

Metaheuristics are considered as modern higher-level algorithms (techniques or strategies) like Genetic Algorithms (GA) as proposed by (Holland, 1975) and modified by (Goldberg, 1989) which is based on principles of genetics and evolution, and mimics the reproduction behaviour observed in biological populations. Simulated Annealing (SA) was proposed by (Kirkpatrick et al., 1983) in which a substance is virtually heated above its melting point and then slowly cooled down to minimize the energy distribution. Geem et al. (2001) proposed Harmony Search (HS) algorithm inspired by the improvisation process of musicians which employed the concept of developing a perfect state of harmony by improvising musical process such as during jazz improvisation. The swarm intelligence based algorithm such as Ant Colony Optimization (ACO) proposed by (Colorni et al., 1991) is motivated by foraging behaviour of real life ant colonies. Particle Swarm Optimization (PSO) developed by (Kennedy and Eberhart, 1995) is basically inspired by social behaviour of animals such as fish schooling or birds flocking. The social based algorithms viz. Teaching-Learning-based optimization (TLBO) proposed by (Rao et al., 2011) is a population based algorithm which mimics the teaching-learning process of the class room. Imperialist Competitive Algorithm (ICA) proposed by (Atashpaz-Gargari and Lucas, 2007) is based on the socio-political relationship amongst the countries. Aforementioned techniques utilize two major components intensification (exploitation) and diversification (exploration) to obtain optimal or near optimal solution (Yang, 2009). Classification of optimization tools and techniques has been highlighted in Fig. 1.1.

Now-a-days, these metaheuristics techniques are enormously being applied to solve different optimization problems in various fields such as industrial planning, scheduling, decision making and pattern recognition, process parameter selection in machining etc. The application of aforementioned techniques in machining performance optimization for both conventional and nonconventional machining has been tabulated in Table 1.1.

Table 1.1: Application of metaheuristics techniques in machining parameters optimization

Machining process(s)	Evolutionary Techniques
Drilling	GA (Jayabal and Natarajan, 2010; Kilickap et al., 2011), SA (Satishkumar and Asokan, 2008), PSO (Gaitonde and Karnik, 2012; Garg et al., 2014), HS (Chatterjee et al., 2014)
Milling	GA (Xu et al., 2010); PSO (Li et al., 2008)
Turning	GA (Duran et al., 2008; Prasad et al., 2007), SA (Kolahan and Abachizadeh, 2008); PSO (Bharathi and Baskar, 2011; Xi and Liao, 2009), ACO (Cus et al., 2009; Vijayakumar et al., 2003)
End milling	GA (Palanisamy et al., 2007; Parent et al., 2007); SA (Zain et al., 2010); PSO (Farahnakian et al., 2011); ACO (Kadirgama et al., 2010)
EDM	GA (Maji and Pratihar, 2010; Gao et al., 2008; Mandal et al., 2007); SA (Yang et.al., 2009)
ECM	GA (Jain and Jain, 2007); PSO (Rao et al., 2008)
WEDM	GA (Mahapatra and Patnaik, 2007; Varun and Venkaiah, 2015); SA (Chen et al., 2010); TLBO (Rao and Kalyankar, 2013)

In the context of applying evolutionary algorithms for machining performance optimization of CFRP composites; it is to be noted that these algorithms can provide the global optima; however, the predicted optimal setting may not be feasible to achieve in practice. This is because; these algorithms follow continuous search in the factorial domain rather than discrete search. In most of the machines/experimental setups, provision is generally given to adjust/tune the controllable process parameters at some discrete levels.

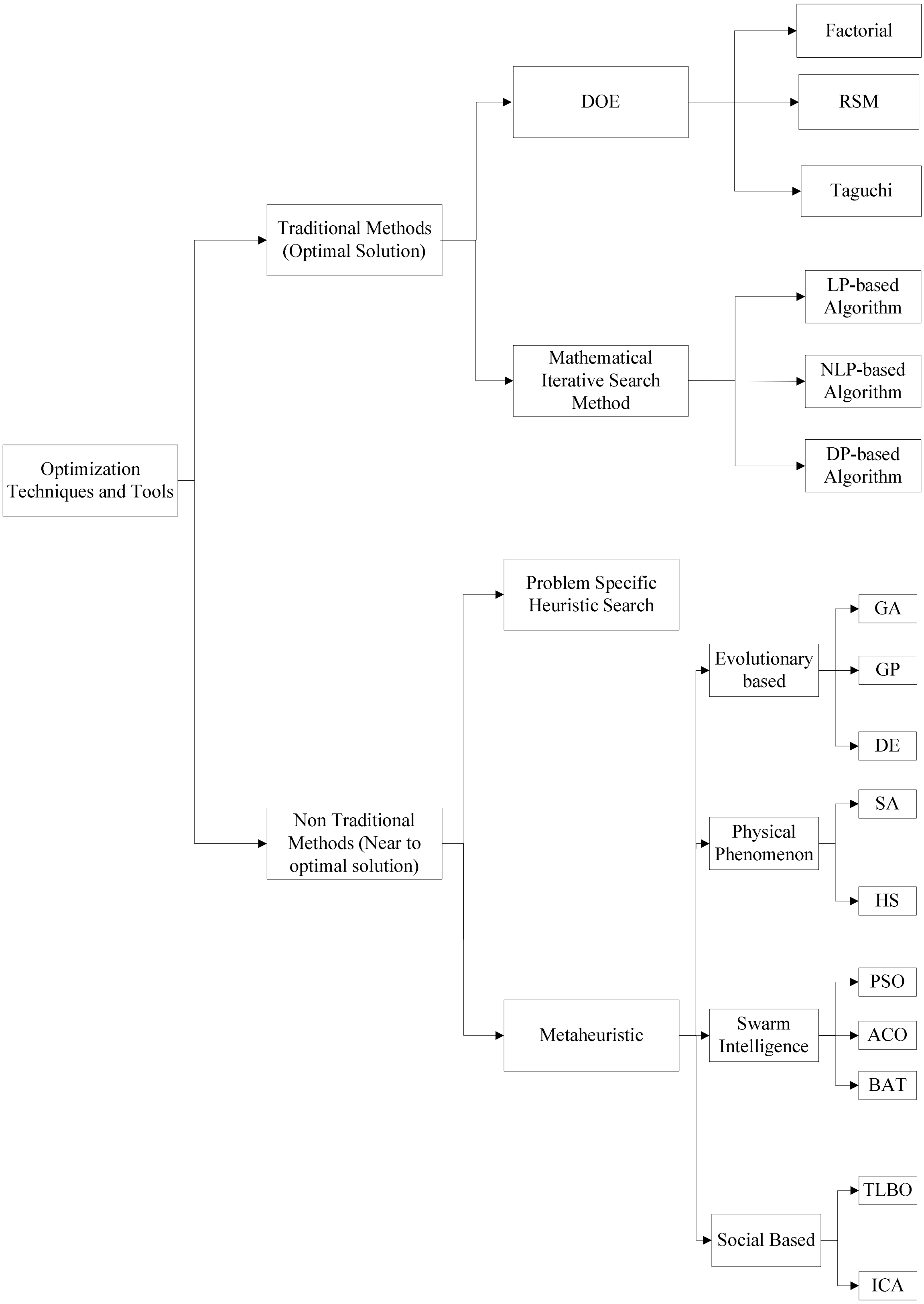


Fig. 1.1: Classification of optimization tools and techniques

Taguchi method (Datta et al., 2008a) is very popular for optimizing process/product in the field of manufacturing/production engineering. The specialty of this approach is that it assumes a discrete search philosophy within available factorial settings and thus provides a near-optimal solution. The predicted near-optimal setting may not always correspond to the global-optima but it is considered to be the best setting amongst available alternative settings in the machine/setup. However, the shortcoming of Taguchi method is that this method fails to solve multi-response optimization problems. In reality, several machining performance features (may be conflicting in nature with respect to one another) may require to be optimized simultaneously. In order to overcome this, multiple responses need to be aggregated to obtain an equivalent single objective function thus to convert a multi-response optimization problem into an equivalent single objective optimization situation. The equivalent single objective function (overall performance index) is optimized finally by Taguchi method. Literature highlights that grey relation analysis (Datta et al., 2008b), desirability function approach (Derringer and Suich, 1980; Datta et al., 2006), utility theory (Kumar et al., 2000; Walia et al., 2006), TOPSIS, MOORA (Gaddakh et al., 2013) etc. can be applied to aggregate multi-responses to transform them into an equivalent single index to be optimized finally by Taguchi method.

However, aforesaid approaches are not free from limitations. These approaches rely on the assumption of negligible response correlation. Moreover, while aggregating multiple response features into an equivalent single index, individual response weights need to be assigned. Assignment of response priority weight depends upon the discretion of the decision-maker. This creates uncertainty in decision making.

To get rid of that, the present work intends to propose a PCA-fuzzy-Taguchi integrated optimization approach and to validate its application potential through case experimental researches in machining (turning/drilling) of CFRP composites. Principal Component Analysis (PCA) (Su and Tong, 1997; Datta et al., 2009a, b; Routara et al., 2010; Liao, 2006) has been explored here to eliminate response correlation and to convert correlated responses into uncorrelated quality indices called individual principal components. Individual principal components have been fed to a Fuzzy Inference System (FIS) (Lu and Anatony, 2002) to transform multi-inputs into a single representative output called as Multi-Performance Characteristic Index (MPCI). FIS works on a rule base by mapping of inputs-output(s), and does not require individual response weights to be provided during aggregation of multiple inputs into a single output. The MPCI as obtained by FIS has been finally optimized by Taguchi method.

The objectives of the present dissertation have been pointed out below.

1. Exploration of Deng's similarity measure approach in combination with Taguchi philosophy, and to compare the optimal setting to that of TOPSIS.
2. To investigate application feasibility of evolutionary algorithms viz. Harmony Search (HS), Teaching-Learning based Optimization (TLBO), Imperialist Competitive Algorithm (ICA) in combination with nonlinear regression and Fuzzy Logic.
3. To propose a PCA-Fuzzy-Taguchi based integrated optimization module for correlated multi-response optimization in machining of CFRP composites.

1.4 Organization of the Present Dissertation

The dissertation has been organized as follows:

Chapter 1 (Background and Rationale) provides a brief introduction on importance of machining and machinability aspects of Carbon Fiber Reinforced Polymer (CFRP) composites. An extensive literature review has been carried out at this stage to study prior state of art in the field of machining GFRP as well as CFRP composites. Based on the literature survey, specific research gaps have been identified. Objectives of the present dissertation have been highlighted too.

Chapter 2 (Experimental Investigations on Drilling: Parametric Optimization) has been divided into three sub-chapters. This chapter deals with parametric appraisal and multi-response optimization in drilling of composites.

The first part highlights an experimental investigation and data analysis on multi-response optimization during drilling of GFRP, CFRP and carbon dust particulate epoxy composites. Application feasibility of Deng's similarity measure approach has been compared to that of TOPSIS in conjugation with Taguchi's robust design philosophy.

The second part of this chapter exhibits application of fuzzy embedded Harmony Search (HS) algorithm for multi-response optimization in drilling of CFRP (Polyester) composites.

The third part of this chapter proposes a PCA-Fuzzy-Taguchi integrated optimization module for optimizing correlated multi-response optimization during drilling of CFRP (epoxy) composites.

Chapter 3 (Experimental Investigations on Turning: Parametric Optimization) exhibits experimental studies on machining (turning) aspects of CFRP composites. This chapter has been structured into four sub-chapters.

The first part of this chapter focuses on application potential of TLBO algorithm for multi-response optimization during turning of CFRP (epoxy) composites.
The second part of this chapter describes a case experimental research on optimization of machining (turing) parameters for CFRP (epoxy) composites by using an integrated optimization route combining Fuzzy Inference System (FIS), nonlinear regression and Imperialist Competitive Algorithm (ICA). The performance of the proposed optimization module has been compared to that of Genetic Algorithm (GA) and Taguchi's robust optimization philosophy.
The third part of this chapter attempts to examine application potential of fuzzy based Harmony Search (HS) algorithm for parametric optimization in turning of CFRP (epoxy) composites. The result obtained thereof, has been compared to that of GA.
The last part of this chapter proposes application potential of PCA-Fuzzy-Taguchi integrated optimization approach in comparison with HS and TLBO for optimizing machining performances during turning of CFRP (epoxy) composites.

Chapter 4 (Conclusions, Thesis Contribution and Suggestions for Future Work) highlights contribution of the present dissertation. Limitations of the present work have been pointed out followed by future research directions.

CHAPTER 2

EXPERIMENTAL INVESTIGATIONS ON DRILLING: PARAMETRIC OPTIMIZATION

2.1 Multi-Response Optimization in Drilling of Composites: Introduction of a Similarity Based Approach in Combination with Taguchi's Philosophy

2.1.1 Coverage

In recent years, the application of polymer composites has been enormously increased particularly in aerospace as well as in automobile sector due to its light weight, high specific stiffness and high specific strength. Machining of those composites has really become an emerging area of research. A considerable volume of research has already been carried out by the pioneers in order to study machining and machinability aspects of these composites, thereby, maintaining both product quality as well as productivity. Drilling is considered as one of the most common machining processes for assembly of composites. In case of Fiber Reinforced Polymer (FRP) composites, delamination and fiber pull out are the major problems that arise during drilling operations. Defect free drilling whilst ensuring satisfactory machining performance (in terms of quality as well as productivity) is definitely a challenging task. In this context, the present study mainly attempts to reduce drilling induced damages and at the same time to improve machining performances during drilling of polymer composites by determining an optimal parametric combination in view of multiple process responses and by considering effects of drilling process control parameters, drill geometry (diameter of drill bit) as well as composite type. Attempt has also been made to understand the relationship (influence) between input-output(s); where, inputs i.e. process parameters have been considered like composite type, drill speed, feed rate, drill diameter and outputs have been and drilling responses like thrust force, torque, delamination at entry and exit and average surface roughness of the drilled hole. Multi-response optimization has been performed using Deng's similarity based method in combination with Taguchi's optimization philosophy. Results obtained thereof have been compared with TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) based Taguchi approach.

2.1.2 Problem Definition

Literature depicts that much work has been highlighted addressing machining process behavior-parametric optimization in GFRP composites, whilst it has been pointed out that lesser attention has been made on aspects of CFRP machining and also to carbon dust reinforced polymer composites. It is obvious that composite type is utmost important (influential) in achieving satisfactory process performances. Therefore, the present work also considers composite type as one of the process variables. The present work highlights the effect of the machining variables such as drill diameter, drill speed, and feed rate (along with composite type) on various process performance indicators like thrust force, torque, roughness average (of the drilled surface) and delamination (in terms of delamination factor both at entry and exit) in drilling of composites. Based on the results from the experiments, an optimal parametric combination has been obtained by using Deng's similarity based approach in combination with Taguchi's optimization module. Degree of similarity approach helps in aggregating multiple performance features in a unique performance index, called overall performance index (OPI), which has been finally optimized by Taguchi's technique. Application feasibility of degree of similarity based Taguchi approach has been compared with TOPSIS based Taguchi method.

2.1.3 Experimental Details

In the present work, series of experiments have been executed in order to collect response values: thrust force, torque, roughness average (R_a), entry delamination factor and exit delamination factor during drilling of different polymer matrix composites (GFRP, CFRP and carbon dust reinforced epoxy composite).

2.1.3.1 Design of Experiments (DOE)

In this research, drilling operations have been performed on CNC drilling machine [MAXMILL 3 axis CNC machine with FANUC Oi Mate MC Controller, Model No. CNC 2000EG]. In order to perform experimentation it is quite necessary to develop a set of experiments for determining the response measurements. For this, Taguchi method has been applied for selecting design of experiment as it examines the effects of entire machining process parameters with less (i.e. limited) number of experiments in comparison to full-factorial design of experiments. The present study focuses on the effects of drilling parameters such as composite type, drill speed, feed rate and drill diameter; each has been varied at three different levels (as shown in Table 2.1). In this experimentation module, L_{27} Orthogonal Array (OA) has been used as shown in Table 2.2.

2.1.3.2 Work Piece and Tool Material

Experimentation has been carried out on three different composite materials such as Carbon Fiber Reinforced Polymer (CFRP), Glass Fiber Reinforced Polymer (GFRP) and Carbon dust reinforced particulate polymer composite plates of thickness 10 mm. For each case, epoxy has been taken as the matrix material. CFRP as well as GFRP composites have been prepared by hand layup (fiber orientation $0/90^0$). Carbon dust particulate epoxy composite has been prepared by injection molding technique. Thermoplastic granules have been fed via a hopper into a screw-like plasticating barrel where melting occurs. The melted plastic has been injected into a heated mold where the part is formed. Epoxy polymer matrix has been prepared by mixing epoxy resin (Ciba-Geigy, araldite LY-556 based on Bisphenol A) and hardener HY-951 (aliphatic primary amine) in wt. ratio 100/12. The ratio of matrix to reinforcing material (77:23); and also the amount of hardener provided have been the same for all composite types. Plate thickness of the specimen composites has been kept constant (10 mm). Carbide drill bit coated with TiAlN of different diameter size such as 6 mm, 8 mm and 10 mm (Manufactured by WIDIA-Hantia) (Fig. 2.1a-2.1c) have been used here. Specimens after performing drilling operations have been shown in Fig. 2.2.

2.1.3.3 Machining Performance Evaluation Characteristics

Drilling operations have been carried out on different composite samples for assessing performance characteristics such as thrust force, torque, entry delamination factor and exit delamination factor. Thrust force is mainly responsible for damages induced during drilling and it may lead to cause delamination and fiber pull put and reduce mainly the performance of FRP composites. Thrust force and Torque has been evaluated by using Digital Drilling Tool Dynamometer [Make: Medilab Enterprises, Chandigarh, INDIA].

Delamination is the failure mechanism of fibrous composites and it can be observed in optical microscope (RADIAL INSTRUMENT with Samsung camera setup, 30-X magnification). The image thus grabbed could be transferred into MATLAB workstation; and the value could be computed through image processing technique in MATLAB (Figs. 2.11, 2.12). Mathematically it can be evaluated as follows:

$$F_d = D_{\max}/d \qquad (2.1)$$

Here, F_d = delamination factor, $D_{\max}$ = maximum diameter observed in the damaged zone, d = diameter of the drill.

The quality of a manufactured product can be evaluated in terms of surface roughness and its measure is roughness average (R_a value). It may be defined as measure of the level of unevenness of the machined surface. Here, the roughness average values of the drilled specimens have been measured by using surface roughness tester SJ-210 (Make: Mitutoyo). It is based on carrier modulating principle having stylus which skids over the machined surface to measure its unevenness. Its mathematical formula has been provided below (Fig. 2.13).

$$R_a = \frac{1}{l}\int_0^l \left| f(X) dx \right| \tag{2.2}$$

Three values for R_a have been computed at different places of the machined surface for a particular work piece and average of these values has been taken for further analysis. Experimental data have been furnished in Table 2.3.

2.1.4 TOPSIS

Hwang and Yoon (1981) proposed TOPSIS for evaluating the alternatives before the multiple attribute decision making; based on fact that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from negative ideal solution. Positive ideal solution compromises of best performance values demonstrated (in the decision matrix) by any alternative for each attribute; whereas, negative ideal solution is the composition of the worst performance values. Procedural steps of TOPSIS are as follows:

Step 1: Establishment of decision Matrix:

$$D = \begin{array}{c} A_1 \\ A_2 \\ . \\ A_i \\ . \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & . & x_{1j} & x_{1n} \\ x_{21} & x_{22} & . & x_{2j} & x_{2n} \\ . & . & . & . & . \\ x_{i1} & x_{i2} & . & x_{ij} & . \\ . & . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mj} & x_{mn} \end{bmatrix} \tag{2.3}$$

Here, $A_i\,((i=1,2,.......,m)$ represents the possible alternatives; $x_j\;(j=1,2,........,n)$ represents the attributes relating to alternative performance, $j=1,2,.........,n$ and x_{ij} is the performance of A_i with respect to attribute $X_{j.}$

Step 2: Normalization of matrix:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{2.4}$$

Here, r_{ij} represents the normalized performance of A_i with respect to attribute X_j.

Step 3: Weighted Decision matrix:

$$V = \lfloor v_{ij} \rfloor V = w_j r_{ij}$$

$$D = \begin{bmatrix} y_{11} & y_{12} & . & y_{1j} & y_{1n} \\ y_{21} & y_{22} & . & y_{2j} & y_{2n} \\ . & . & . & . & . \\ y_{i1} & y_{i2} & . & y_{ij} & . \\ . & . & . & . & . \\ y_{m1} & y_{m2} & . & y_{mj} & y_{mn} \end{bmatrix} \tag{2.5}$$

Here, $\sum_{j=1}^{n} w_j = 1$

Step 4: Determine the ideal (best) and negative ideal (worst) solutions:

a) The ideal solution:

$$A^+ = \left\{ \left(\max_i y_{ij} \middle| j \in J \right), \left(\min_i y_{ij} \middle| j \in J' \middle| i = 1, 2, \dots\dots\dots\dots, m \right) \right\} \tag{2.6}$$

$$= \left\{ y_1^+, y_2^+, \dots\dots\dots, y_j^+, \dots\dots y_n^+ \right\}$$

b) The negative ideal solution:

$$A^- = \left\{ \left(\min_i y_{ij} \middle| j \in J \right), \left(\max_i y_{ij} \middle| j \in J' \middle| i = 1, 2, \dots\dots\dots, m \right) \right\} \tag{2.7}$$

$$= \left\{ y_1^-, y_2^-, \dots\dots\dots, y_j^-, \dots\dots y_n^- \right\}$$

Here,

$J = \left\{ j = 1,2,\dots\dots\dots, n \middle| j \right\}$: Associated with the beneficial attributes

$J^{'} = \{ j = 1,2,......., n | j \}$: Associated with non-beneficial attributes

Step 5: Determine the distance measures. The separation of each alternative from the ideal solution is given by n- dimensional Euclidean distance from the following equations:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^+ \right)^2} \quad i = 1, 2, ...,m \tag{2.8}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^- \right)^2} \quad i = 1, 2, ...,m \tag{2.9}$$

Step 6: Calculate the Overall performance coefficient closest to the ideal solution:

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-}, \quad i = 1, 2,........., m; 0 \leq C_i^+ \leq 1 \tag{2.10}$$

2.1.5 Deng's Similarity Based Approach

Hepu Deng (2007) proposed a new approach to find out the best alternative of the multi criteria decision problem. In some cases TOPSIS was found inefficient because comparing the distance between two alternatives was not sufficient. Deng discovered that, the comparison would be more effective, if magnitude and conflict between the alternative and ideal solution are taken in to consideration. Gradients of the variables indicate the conflicts and from the rank of conflict index, the best alternative can be identified.

Deng's similarity based method (Safari et al., 2013) is a modified form of TOPSIS methodology based on concept that ideal solution is used in such manner so that most preferred alternative should have the highest degree of similarity to the positive ideal increasing or decreasing values (Refer Figs. 2.3a-2.3c). It is proposed for evaluating the conflicting index between two alternatives to show the degree conflict between the alternatives.

The steps for the method are similar to TOPSIS up to step 4. Further steps can be expressed as:

Steps involved in Deng's Similarity-Based Method

Step 1: Formulation of decision matrix

Step 2: Normalization of decision matrix

Step 3: Determination of weighted decision matrix

Step 4: Evaluation of Positive ideal and negative ideal solution

Step 5: Calculate degree of conflict between each alternative and positive ideal solution and negative ideal solution.

Conflict between the alternative and positive ideal solution can be obtained as:

$$\cos\theta_i^+ = \frac{\sum_{j=1}^{m} y_{ij} y_j^+}{\left(\sum_{j=1}^{m} y_{ij}{}^2\right)^{0.5} \left(\sum_{j=1}^{m} y_{ij}^{+2}\right)^{0.5}} \tag{2.11}$$

Conflict between the alternative and negative ideal solution can be obtained as:

$$\cos\theta_i^- = \frac{\sum_{j=1}^{m} y_{ij} y_j^-}{\left(\sum_{j=1}^{m} y_{ij}{}^2\right)^{0.5} \left(\sum_{j=1}^{m} y_j^{-2}\right)^{0.5}} \tag{2.12}$$

Here the value of θ lies between 0° and 90°

Step 6: Calculate the degree of similarity between the alternatives and positive and negative ideal solution:

$$|C_i| = \cos\theta_i^{-+} \times |A_i| \tag{2.13}$$

$$|C_i| = \frac{\sum_{j=1}^{m} y_{ij} y_j^{-+}}{\left(\sum_{j=1}^{m} y_{ij}{}^2\right)^{0.5} \left(\sum_{j=1}^{m} y_i^{-+2}\right)^{0.5}} \times \left(\sum_{j=1}^{m} y_{ij}^2\right)^{0.5} \tag{2.14}$$

$$S_i^{-+} = \frac{|C_i|}{|A^{-+}|} = \frac{\cos\theta^{-+} \times |A_i|}{|A^{-+}|} = \frac{\cos\theta^{-+} \times \left(\sum_{j=1}^{m} y_{ij}^2\right)^{0.5}}{\left(\sum_{j=1}^{m} y_j^{-+2}\right)^{0.5}} \quad (2.15)$$

Step 7: Calculate the overall performance index for each alternative:

$$P_i = \frac{S_i^+}{S_i^+ + S_i^-}, \; i = 1,2,........,n \quad (2.16)$$

Step 8: Rank the alternative in descending order of the index value. Larger P_i indicates a good performance of the alternative A_i.

2.1.6 Results and Discussions

2.1.6.1 Effects of Machining Parameters on Output Performance Characteristics

Attempt has been made to examine the effects of process variables such as composite type, drill rotational speed, feed rate and drill diameter on output response parameters such as thrust force, torque, delamination factor (at entry and exit) and surface roughness (roughness average). In order to determine the significant factors; the application of Taguchi has been recommended for analyzing the mean values of Signal-to-Noise (S/N) ratio which makes the analysis simpler. Here, for each output response Lower-is-Better (LB) criterion has been selected for further analysis. ANOVA has been performed to investigate the main effects of process variables as well as parametric interaction effects on these performance evaluation characteristics. The effect of main factors and their interactions have been checked by using analysis of variance (ANOVA). From ANOVA table (Table 2.4), it has been noticed that composite type and drill diameter bear significant effect on torque; whereas, drill speed showed more effect on thrust force. It has also been noticed that composite type appears also significant on damaged induced at entry and exit and also on the average surface roughness (Table 2.5). Main effect and interaction plots have also been furnished in Figs. 2.4-2.8.

2.1.6.2 Parametric Optimization

TOPSIS as well as Deng's similarity based Taguchi method have been applied individually to evaluate the optimal parametric combination in drilling of polymer composites. After experimentation, the output response characteristics have been measured and presented accordingly in Table 2.3. The experimental data have been normalized so that all the response features came into a single dimensionless scale in between 0 to 1. Computed normalized data have been tabulated in Table 2.6. On the basis of priority, appropriate weight must be assigned to each response feature. In this study, each response parameters has been assumed equally important and therefore, they have been assigned equal priority weight. The weighted normalized decision matrix has been presented in Table 2.7. In order to assess the separation distance, it has been necessary to evaluate the deviation from ideal solution which has been expressed in terms of positive ideal solution and negative ideal solution. In Deng's degree of similarity method for evaluation of closeness coefficient it is necessary to show the conflict between the alternatives and ideal solution. Table 2.8 presents the positive and negative conflicting criteria among the alternatives and ideal solutions. Finally, overall performance index (OPI) has been computed by TOPSIS has been shown in Table 2.9. Similarly, OPI thus computed by Deng's method has been furnished in Table 2.10. It has been clear from Tables 2.9-2.10 that application of Deng's similarity solution reduces the variation among the values of OPI. Taguchi acclaims analyzing of the mean values of Signal-to-Noise (S/N) ratio using conceptual method which is essentially done through plotting the effects and identifying the factors that appears to be significant. Further, based on the S/N ratios, the optimal parametric combination has been determined for each methodology as follows (Table 2.11). S/N ratio plot for evaluating optimal setting has been shown in Fig. 2.9 (for TOPSIS based Taguchi method) and Fig. 2.10 (for Deng's similarity method combined with Taguchi). It has also been noticed that predicted S/N ratio value for each optimal conditions (obtained from aforesaid two methodologies) appeared as the highest amongst all S/N ratios obtained in the experiments that have been presented in Tables 2.9-2.10. Therefore, quality has been found improved. This is because S/N ratio should always be maximized as per Taguchi's philosophy.

2.1.7 Concluding Remarks

In the present work, attempts have been made for investigating the influence of process parameters on performance responses to evaluate the optimal machining combination (parameters settings) during drilling of polymer composites. It has been noticed that the type of composite showed remarkably significant effect on drilling performance characteristics like thrust force, torque, damage induced at entry and exit (delamination factor) and average surface roughness of the drilled hole. It has been observed that the optimal combination derived from each methodology (TOPSIS and Deng's similarity solution) appears same. It was also noticed that range of OPI for Deng's similarity solution varied less as compared to TOPSIS. Therefore, it can be concluded that Deng's similarity measure approach in conjugation with Taguchi's philosophy can be applied as an efficient alternative for solving multi-response optimization problems in composite machining. It can also be applied for continuous quality improvement for a process/product and can be explored to facilitate off-line quality control.

Fig. 2.1a: Drill bit (ϕ10 mm)

Fig. 2.1b: Drill bit (ϕ8 mm)

Fig. 2.1c: Drill bit (ϕ6 mm)

Fig. 2.2: Specimens after performing drilling operations

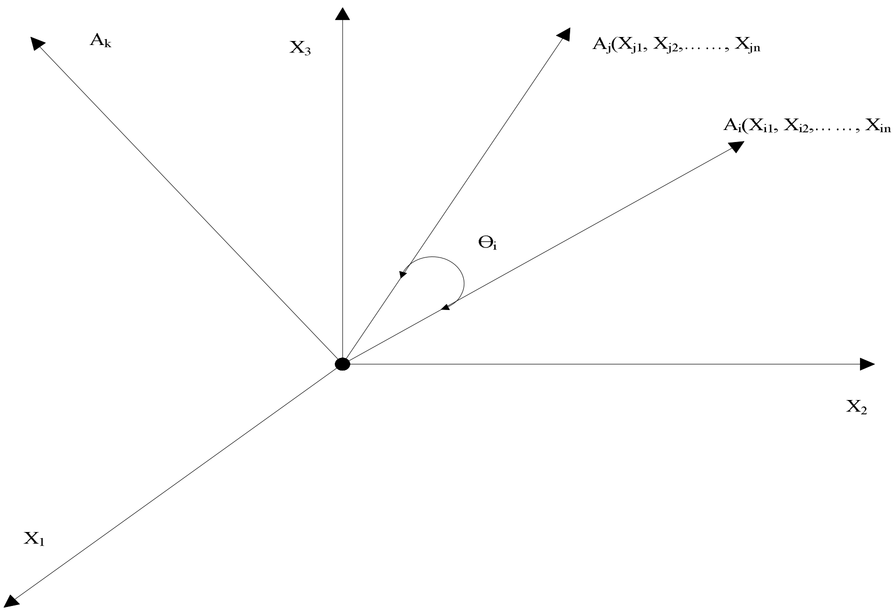


Fig. 2.3a: Degree of conflict between alternatives by gradients

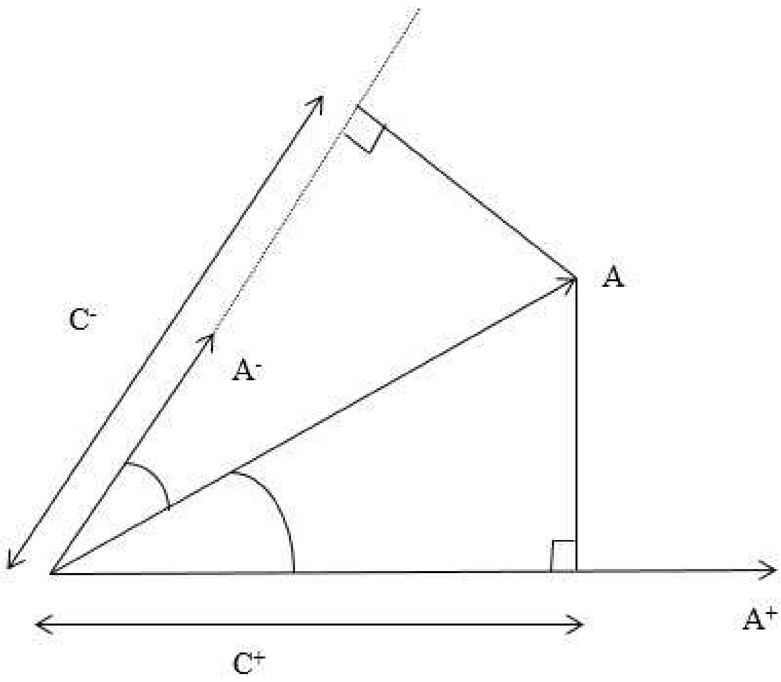


Fig. 2.3b: Degree of conflict between A_i and $A^{\pm}$

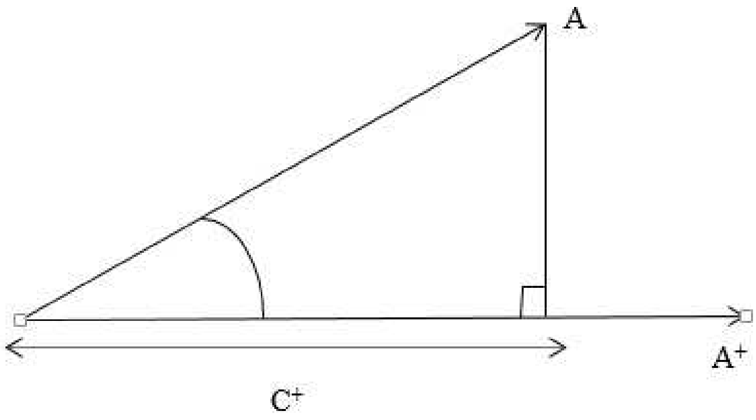


Fig. 2.3c: Degree of conflict between A_i and A^{+}

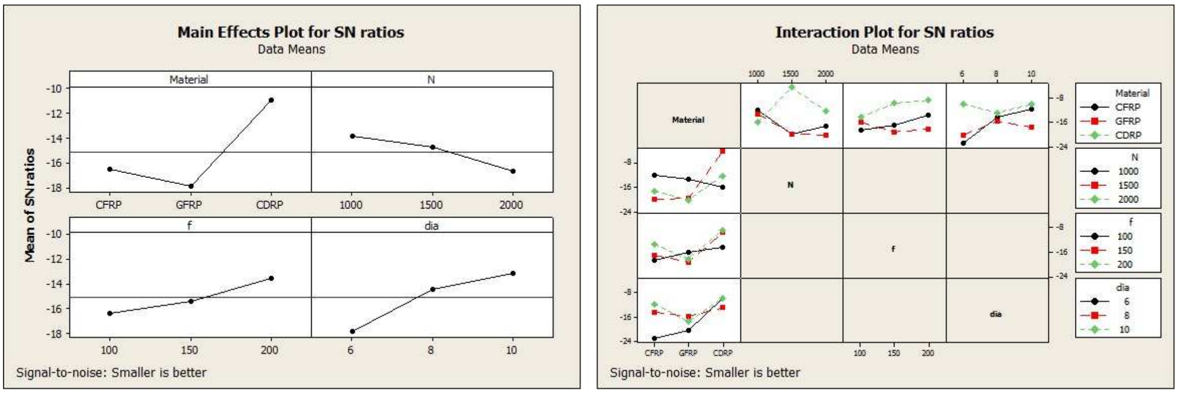


Fig. 2.4: Main effect plot and interaction plot for torque

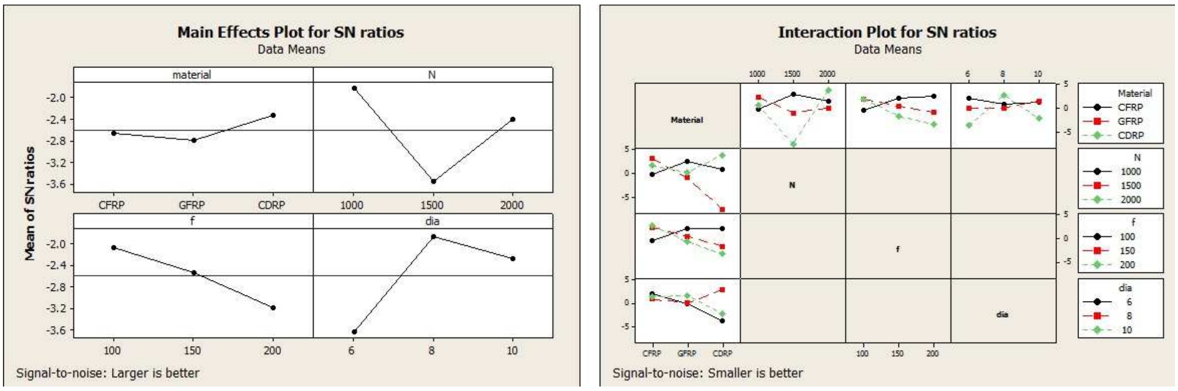


Fig. 2.5: Main effect plot and interaction plot for Thrust force

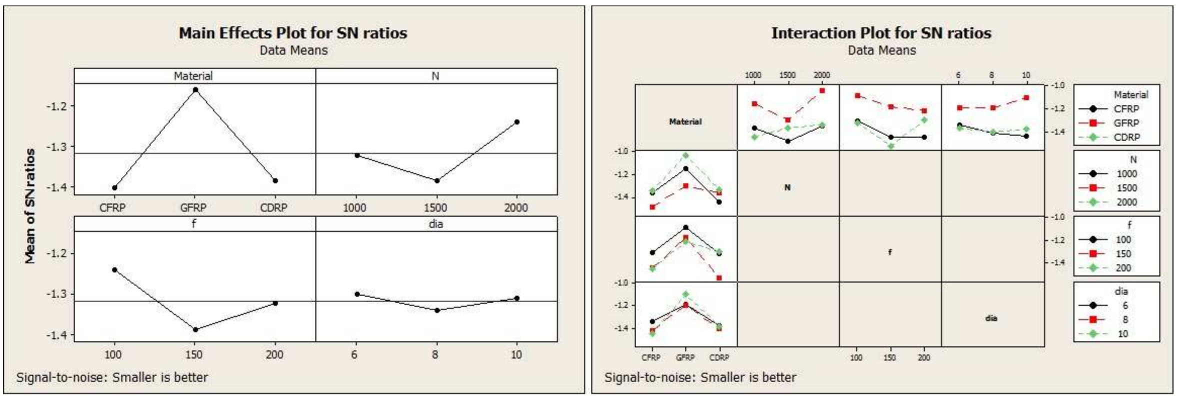


Fig. 2.6: Main effect plot and interaction plot for delamination at entry

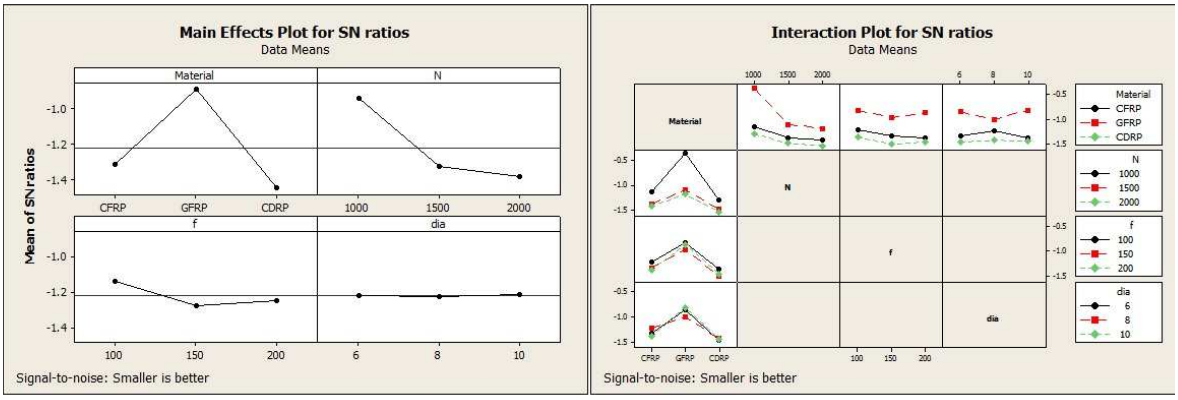


Fig. 2.7: Main effect plot and interaction plot for delamination at exit

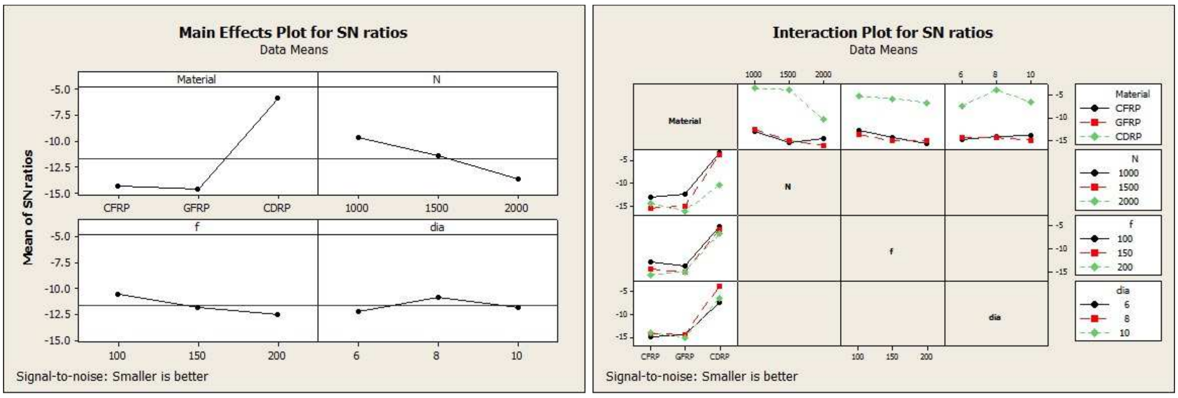


Fig. 2.8: Main effect plot and interaction plot for roughness average

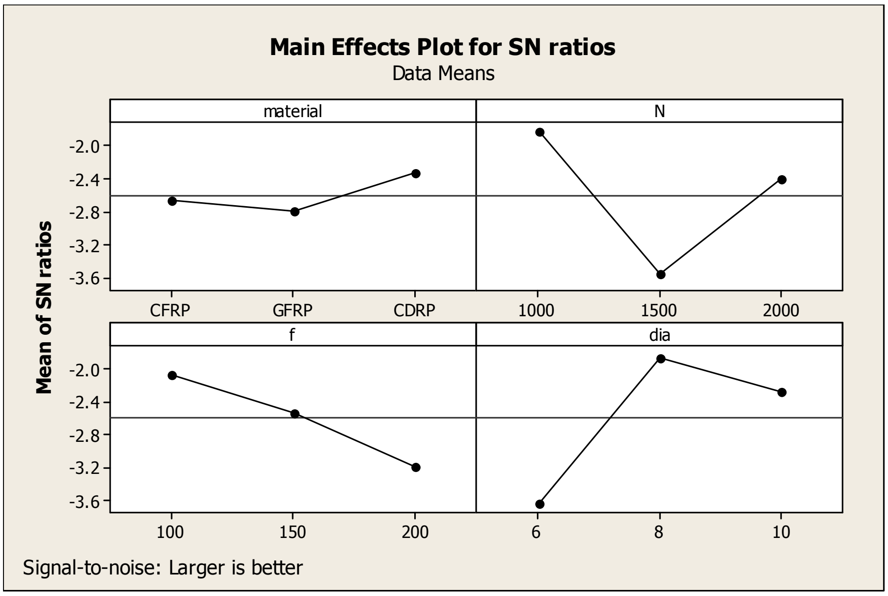


Fig. 2.9: Optimal parametric combination by using TOPSIS

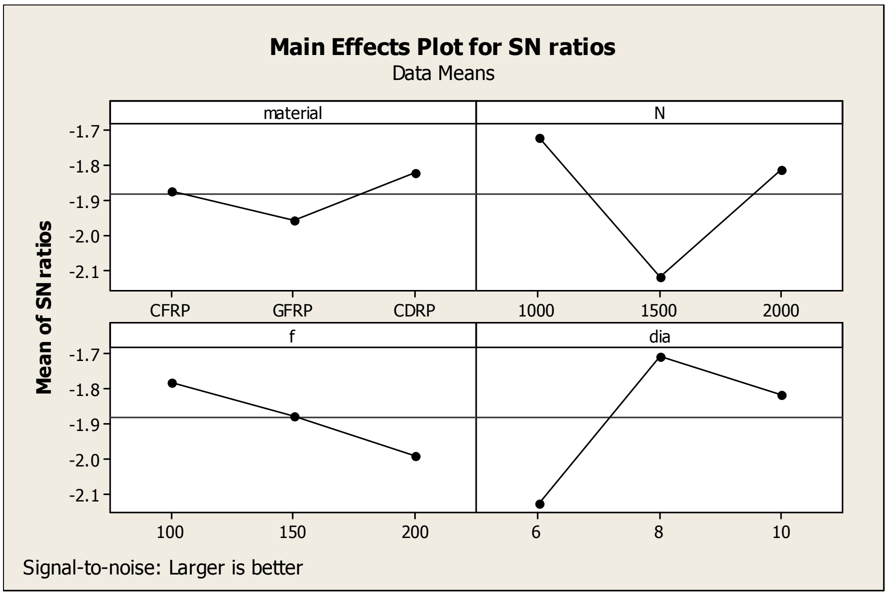


Fig. 2.10: Optimal parametric combination by using Deng's similarity measure approach

Table 2.1: Domain of experiments

Factors (Notation)	Unit	Level 1	Level 2	Level 3
Material (M)	-	CFRP	GFRP	Carbon dust
Drill Speed (N)	[RPM]	1000	1500	2000
Feed rate (f)	[mm/min]	100	150	200
Drill diameter (d)	[mm]	6	8	10

Table 2.2: Design of experiment (L_{27} Orthogonal Array)

Sl. No.	Parametric Settings			
	Material (M) (Composite Type)	N [RPM]	f [mm/min]	d [mm]
1	CFRP	1000	100	6
2	CFRP	1000	150	8
3	CFRP	1000	200	10
4	CFRP	1500	100	8
5	CFRP	1500	150	10
6	CFRP	1500	200	6
7	CFRP	2000	100	10
8	CFRP	2000	150	6
9	CFRP	2000	200	8
10	GFRP	1000	100	6
11	GFRP	1000	150	8
12	GFRP	1000	200	10
13	GFRP	1500	100	8
14	GFRP	1500	150	10
15	GFRP	1500	200	6
16	GFRP	2000	100	10
17	GFRP	2000	150	6
18	GFRP	2000	200	8
19	CDRP	1000	100	6
20	CDRP	1000	150	8
21	CDRP	1000	200	10
22	CDRP	1500	100	8
23	CDRP	1500	150	10
24	CDRP	1500	200	6
25	CDRP	2000	100	10
26	CDRP	2000	150	6
27	CDRP	2000	200	8

Table 2.3: Experimental data

Sl. No.	Torque [kN-mm]	Thrust [kN]	R_a [μm]	F_{in}	F_{out}
1	1.39	0.161	4.177	1.160638887	1.12959444
2	0.38	0.076	4.476	1.174264929	1.13598854
3	0.13	0.095	4.919333	1.177395832	1.15975694
4	0.79	0.098	4.828	1.170781249	1.14763021
5	0.76	0.088	5.966667	1.210468748	1.1818276
6	1.73	0.043	7.418	1.180736196	1.18801224
7	0.63	0.079	4.238667	1.156414374	1.17739583
8	1.33	0.073	5.675333	1.160224374	1.1826875
9	0.52	0.105	6.373	1.187979165	1.17475
10	0.47	0.08	3.556667	1.146174999	1.02549854
11	0.58	0.09	4.641667	1.125775624	1.06833458
12	0.4	0.062	4.705667	1.152577915	1.03769583
13	0.53	0.081	5.046333	1.167870832	1.14873264
14	1.07	0.118	6.085333	1.16742986	1.12959444
15	1.81	0.154	6.157667	1.148732637	1.12990312
16	1.06	0.083	6.396667	1.086511457	1.12960547
17	1.39	0.086	6.669333	1.143959113	1.15831276
18	0.81	0.143	6.26	1.148754686	1.15351719
19	0.65	0.088	1.379333	1.177461978	1.15831276
20	0.7	0.103	1.402667	1.214437498	1.1679039
21	0.58	0.09	1.714	1.153517186	1.16145469
22	0.41	0.072	1.109667	1.148767915	1.17170729
23	0.101	0.3	1.393667	1.195916665	1.20168458
24	0.117	0.7	2.419667	1.16789729	1.19086312
25	0.56	0.084	4.002333	1.167914929	1.18065903
26	0.42	0.062	3.789333	1.168576387	1.20385417
27	0.32	0.054	2.452667	1.164166665	1.19944444

Table 2.4: ANOVA table for torque and thrust force

Source	DF	Seq SS		Adj MS		P-Value	
		Torque	Thrust force	Torque	Thrust force	Torque	Thrust force
M	2	1.21598	0.03618	0.607990	0.01809	0.011	0.336
N	2	0.27142	0.05346	0.135710	0.02673	0.176	0.024
f	2	0.00600	0.02281	0.003000	0.01140	0.950	0.482
d	2	1.27402	0.02306	0.637010	0.01153	0.010	0.477
M*N	4	1.12466	0.10569	0.281164	0.02642	0.043	0.027
M*f	4	0.30016	0.04294	0.075040	0.01073	0.368	0.578
M*d	4	1.06634	0.04288	0.266586	0.01072	0.048	0.577
Residual Error	6	0.34654	0.08269	0.057756	0.01378		
Total	26	5.60512	0.40970				

Table 2.5: ANOVA table for damage induced at entry and exit and average surface roughness

Source	DF	Seq SS			Adj MS			P-Value		
		Fin	Fout	Ra	Fin	Fout	Ra	Fin	Fout	Ra
M	2	0.00587	0.025930	62.983	0.002936	0.012965	31.491	0.047	0.000	0.000
N	2	0.00169	0.017380	12.608	0.000846	0.008690	6.3042	0.001	0.000	0.001
f	2	0.001778	0.001596	3.453	0.000889	0.000798	1.7265	0.338	0.006	0.032
d	2	0.000138	0.000005	1.221	0.000002	0.000002	0.6107	0.903	0.963	0.185
M*N	4	0.001154	0.005954	5.033	0.000069	0.001489	1.2583	0.020	0.001	0.047
M*f	4	0.001177	0.000357	2.682	0.000089	0.000089	0.6704	0.781	0.316	0.153
M*d	4	0.000481	0.001665	1.171	0.000294	0.000416	0.2929	0.942	0.020	0.441
Residual Error	6	0.004080	0.000361	1.616	0.000600	0.000060	0.2693			
Total	26	0.016373	0.053248	90.767						

Table 2.6: Normalized data

Sl. No.	Thrust	Torque	R_a	F_{in}	F_{out}
1	0.179402107	0.311683559	0.170528665	0.191867638	0.188623198
2	0.084686709	0.085208455	0.182735529	0.194120188	0.189690905
3	0.105858386	0.029150261	0.200834879	0.194637764	0.193659827
4	0.109201282	0.177143893	0.197106152	0.193544293	0.191634866
5	0.098058294	0.17041691	0.243592952	0.200105117	0.197345254
6	0.047914848	0.387922703	0.302844539	0.195189966	0.198377984
7	0.088029605	0.141266649	0.173046259	0.191169275	0.196605223
8	0.081343812	0.298229593	0.231699057	0.191799114	0.197488842
9	0.117001374	0.116601044	0.260181753	0.196387317	0.196163414
10	0.089143904	0.105389405	0.145203178	0.189476583	0.17124094
11	0.100286892	0.13005501	0.189498989	0.186104319	0.178393836
12	0.069086526	0.089693111	0.19211183	0.190535062	0.173277682
13	0.090258203	0.118843372	0.206019734	0.193063166	0.191818954
14	0.131487258	0.239929071	0.248437566	0.192990268	0.188623198
15	0.171602015	0.405861325	0.251390647	0.189899391	0.188674743
16	0.0924868	0.237686743	0.261147973	0.179613478	0.188625039
17	0.095829697	0.311683559	0.272279735	0.18911027	0.193418672
18	0.159344728	0.181628549	0.255568457	0.189903036	0.192617893
19	0.098854547	0.145751305	0.056312142	0.194648698	0.193418672
20	0.114772776	0.156962943	0.057264767	0.200761199	0.195020232
21	0.100286892	0.13005501	0.069975133	0.190690335	0.193943321
22	0.080229513	0.091935438	0.045302857	0.189905223	0.195655333
23	0.33428964	0.02264751	0.056897336	0.197699481	0.200661034
24	0.780009159	0.026235235	0.098784435	0.19306754	0.198854034
25	0.093601099	0.125570355	0.163397774	0.193070456	0.197150122
26	0.069086526	0.094177766	0.154701915	0.193179803	0.201023318
27	0.060172135	0.071754488	0.100131681	0.192450823	0.200286969

Table 2.7: Weighted normalized data

Sl. No.	Thrust	Torque	R_a	F_{in}	F_{out}
1	0.035880421	0.062336712	0.034105733	0.038373528	0.03772464
2	0.016937342	0.017041691	0.036547106	0.038824038	0.037938181
3	0.021171677	0.005830052	0.040166976	0.038927553	0.038731965
4	0.021840256	0.035428779	0.03942123	0.038708859	0.038326973
5	0.019611659	0.034083382	0.04871859	0.040021023	0.039469051
6	0.00958297	0.077584541	0.060568908	0.039037993	0.039675597
7	0.017605921	0.02825333	0.034609252	0.038233855	0.039321045
8	0.016268762	0.059645919	0.046339811	0.038359823	0.039497768
9	0.023400275	0.023320209	0.052036351	0.039277463	0.039232683
10	0.017828781	0.021077881	0.029040636	0.037895317	0.034248188
11	0.020057378	0.026011002	0.037899798	0.037220864	0.035678767
12	0.013817305	0.017938622	0.038422366	0.038107012	0.034655536
13	0.018051641	0.023768674	0.041203947	0.038612633	0.038363791
14	0.026297452	0.047985814	0.049687513	0.038598054	0.03772464
15	0.034320403	0.081172265	0.050278129	0.037979878	0.037734949
16	0.01849736	0.047537349	0.052229595	0.035922696	0.037725008
17	0.019165939	0.062336712	0.054455947	0.037822054	0.038683734
18	0.031868946	0.03632571	0.051113691	0.037980607	0.038523579
19	0.019770909	0.029150261	0.011262428	0.03892974	0.038683734
20	0.022954555	0.031392589	0.011452953	0.04015224	0.039004046
21	0.020057378	0.026011002	0.013995027	0.038138067	0.038788664
22	0.016045903	0.018387088	0.009060571	0.037981045	0.039131067
23	0.066857928	0.004529502	0.011379467	0.039539896	0.040132207
24	0.156001832	0.005247047	0.019756887	0.038613508	0.039770807
25	0.01872022	0.025114071	0.032679555	0.038614091	0.039430024
26	0.013817305	0.018835553	0.030940383	0.038635961	0.040204664
27	0.012034427	0.014350898	0.020026336	0.038490165	0.040057394

Table 2.8: Positive ideal solution and negative ideal solution

	Thrust force	Torque	R_a	F_{in}	F_{out}
A+	0.00958297	0.004529502	0.009060571	0.035922696	0.034248188
A-	0.156001832	0.081172265	0.060568908	0.04015224	0.040204664

Table 2.9: Computation results in TOPSIS

Sl. No.	S+	S-	D_i	S/N ratio (dB)	Predicted S/N ratio (dB)
1	0.0684	0.124473	0.645362	-3.80393	0.80489
2	0.031435	0.155034	0.831418	-1.60361	
3	0.033656	0.155806	0.82236	-1.69876	
4	0.04529	0.143334	0.759893	-2.38495	
5	0.0509	0.144778	0.739878	-2.61679	
6	0.089606	0.146468	0.620431	-4.14612	
7	0.036208	0.15044	0.80601	-1.87319	

8	0.067125	0.142109	0.679187	-3.36022	
9	0.049265	0.144929	0.746312	-2.5416	
10	0.027294	0.154071	0.84951	-1.41663	
11	0.037505	0.148548	0.798419	-1.95538	
12	0.032631	0.157291	0.828187	-1.63743	
13	0.03872	0.150686	0.795571	-1.98642	
14	0.061948	0.134356	0.684427	-3.29346	
15	0.090561	0.12216	0.574273	-4.81763	
16	0.061683	0.141889	0.696996	-3.13539	
17	0.07428	0.138289	0.650561	-3.73424	
18	0.057434	0.132352	0.697376	-3.13066	
19	0.027268	0.153948	0.849528	-1.41644	
20	0.030768	0.150311	0.830086	-1.61753	
21	0.024921	0.153944	0.860673	-1.30323	
22	0.016183	0.161829	0.909092	-0.82785	
23	0.057737	0.127439	0.688207	-3.24562	
24	0.146939	0.086214	0.369773	-8.64129	
25	0.033154	0.150896	0.819865	-1.72515	
26	0.027279	0.158058	0.852813	-1.38292	
27	0.016219	0.163824	0.909916	-0.81998	

Table 2.10: Computation table in Deng's similarity measure approach

Sl. No.	$Cos\,\theta^{+}$	$Cos\,\theta^{-}$	Di	S/N ratio (dB)	Predicted S/N ratio (dB)
1	0.727905	0.844496	0.764792	-2.32914	-1.07476
2	0.908383	0.687695	0.832858	-1.58858	
3	0.900263	0.670977	0.835023	-1.56603	
4	0.841358	0.765037	0.805776	-1.87571	
5	0.823745	0.731557	0.809442	-1.83629	
6	0.64153	0.662618	0.785053	-2.10202	
7	0.886184	0.723157	0.822153	-1.70095	
8	0.731244	0.721603	0.79265	-2.01837	
9	0.831503	0.734513	0.810264	-1.82747	
10	0.915396	0.724702	0.826539	-1.65473	
11	0.866308	0.7481	0.813726	-1.79043	
12	0.887558	0.668818	0.833503	-1.58185	
13	0.873423	0.713167	0.822066	-1.70187	
14	0.762592	0.790697	0.784403	-2.10922	
15	0.64399	0.808131	0.750384	-2.49433	
16	0.745787	0.737693	0.792262	-2.02262	
17	0.701537	0.736234	0.782352	-2.13195	
18	0.79059	0.816443	0.785081	-2.10171	
19	0.92237	0.718795	0.828789	-1.63112	
20	0.910444	0.744185	0.82191	-1.70351	
21	0.934652	0.725347	0.829378	-1.62495	
22	0.970605	0.650342	0.849172	-1.42009	
23	0.781995	0.855473	0.775197	-2.21175	

24	0.517084	0.897242	0.684943	-3.28691	
25	0.904051	0.725704	0.824544	-1.67572	
26	0.931944	0.660689	0.841801	-1.49581	
27	0.97574	0.615128	0.856813	-1.34228	

Table 2.11: Evaluated optimal settings

Methodology Adapted	Optimal Parametric Combination
TOPSIS based Taguchi	$M_{CDRP} N_{1000} f_{100} d_8$
Deng's similarity based method and Taguchi	$M_{CDRP} N_{1000} f_{100} d_8$

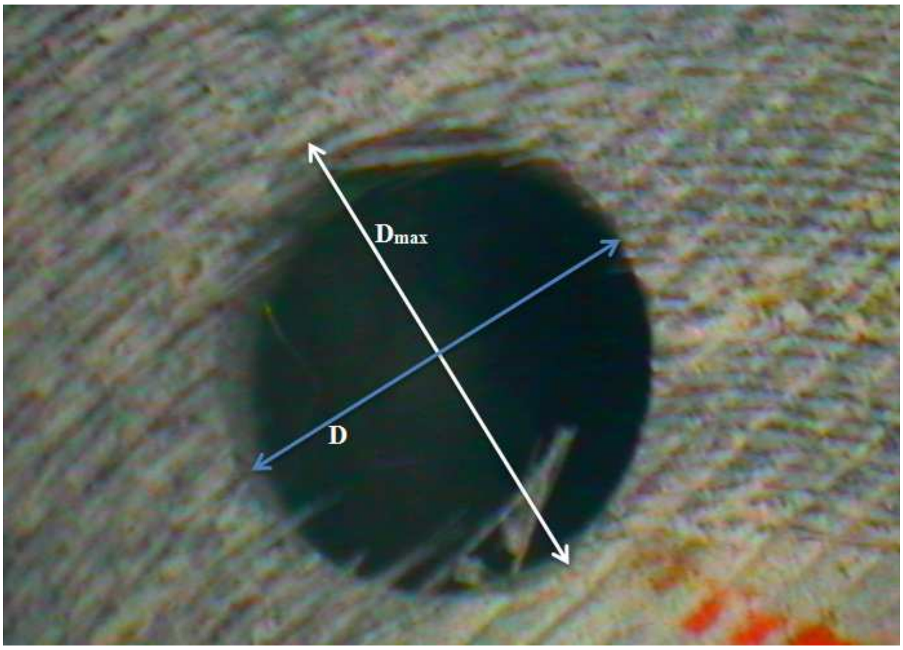
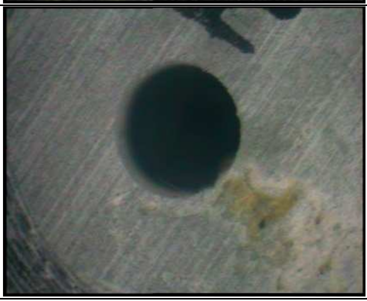
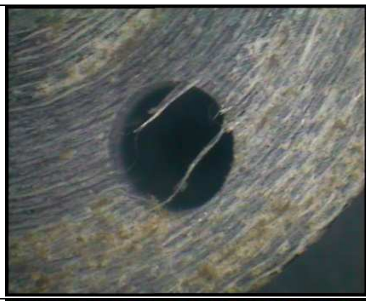
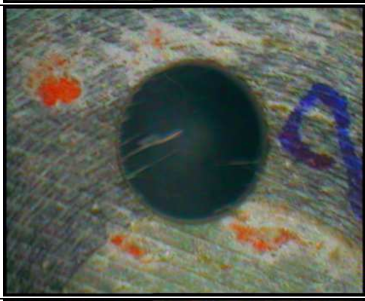
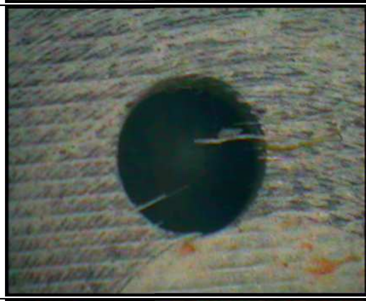
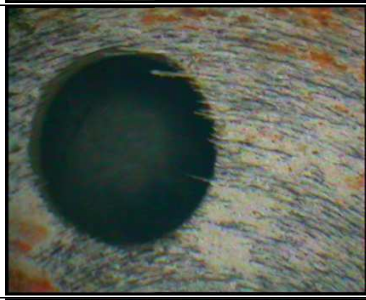
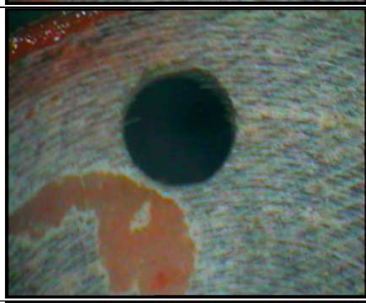
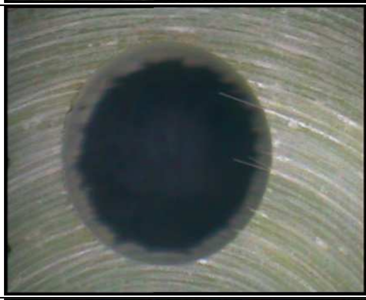


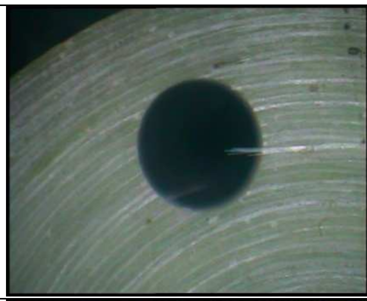
Fig. 2.11: Computation of delamination factor

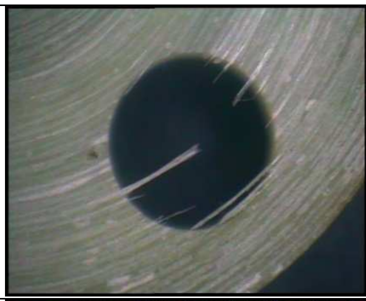
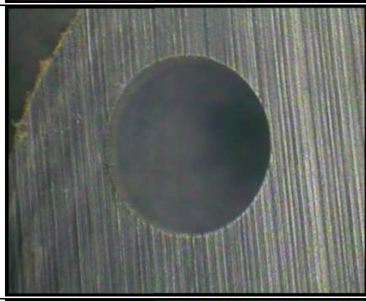
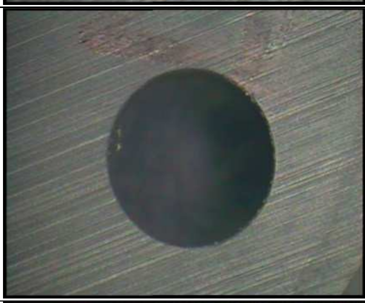
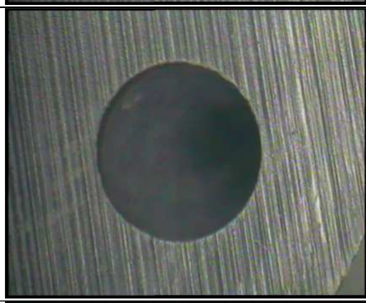
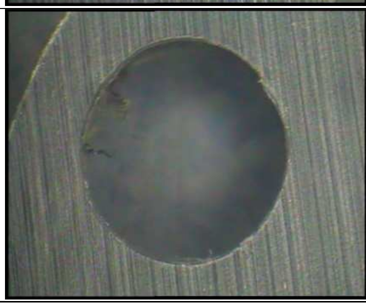
Fig. 2.12: Drilled hole snaps at entry as well as exit

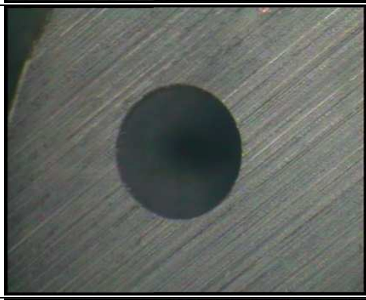
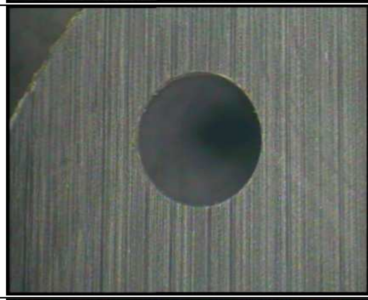
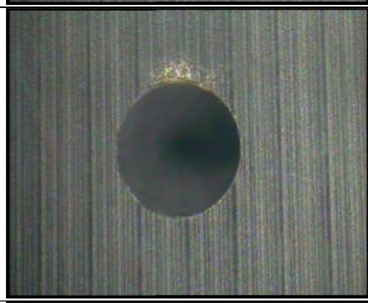
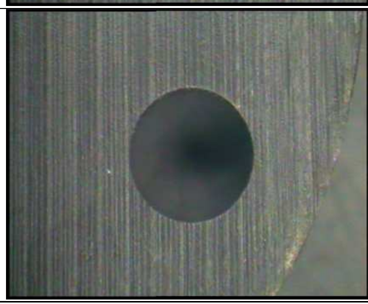
Sl. No.	Entry	Exit
1.		
2.		

3.		
4.		
5.		
6.		
7.		

8.		
9.		
10.		
11.		
12.		

13.		
14.		
15.		
16.		
17.		

18.		
19.		
20.		
21.		
22.		

23.		
24.		
25.		
26.		
27.		

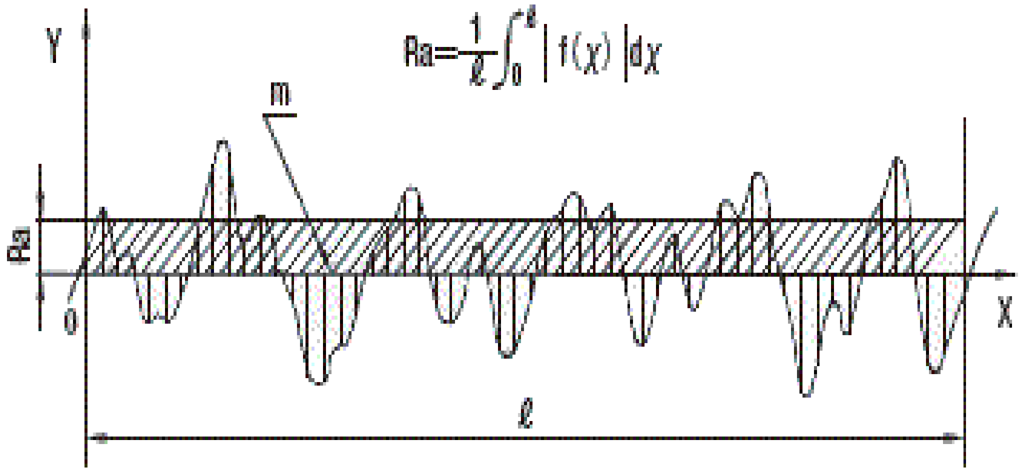


Fig. 2.13: Computation of surface roughness

2.2 Multi-Response Optimization in Drilling of CFRP (Polyester) Composites: Application of a Fuzzy Embedded Harmony Search (HS) Algorithm

2.2.1 Coverage

Widespread application of carbon fiber reinforced polymer (CFRP) composites in automobile, structural and aerospace engineering leads to vital concern for attaining usable shapes with reasonable accuracy through machining and moulding processes. Machining of CFRP composites needs careful planning and estimation of adequate process parameters as it is substantially different from conventional machining of metallic materials. Performance characteristics in machining (drilling) of CFRP composites are greatly influenced by various process parameters such as drill speed, feed and drill diameter. Generally, thrust force, torque, surface roughness and delamination factor (both at entry and exit) are considered as the output performance characteristics in composite drilling. In the present work, the extent of process performance has been evaluated in drilling of CFRP composites using TiAlN coated solid carbide drill bit. Multiple performance characteristics are converted into an equivalent single performance characteristic known as Multi Performance Characteristic Index (MPCI) using a fuzzy inference system (FIS). A non-linear regression model has been developed to express MPCI as a function of the selected process parameters. The regression model has been considered as the fitness function and finally optimized by a latest evolutionary technique known as harmony search (HS) algorithm which is inspired by the improvisation process of musicians. The effectiveness of the proposed algorithm has been compared to that of genetic algorithm (GA) as well as Taguchi's robust optimization philosophy. The results indicate that HS algorithm is quite efficient in searching optimal process parameters at less computational effort as compared to genetic algorithm due to diversity in search mechanism.

2.2.2 Problem Definition

Literature review depicts that considerable work has been carried out by pioneers highlighting machining as well as machinability aspects of CFRP composites. However, sound machining needs exploration of the most favorable process environment (parametric setting) in order to optimize multi-performance characteristics of the machining process. In practice, it is really difficult to evaluate an optimal setting of process parameters considering multiple (may be conflicting in nature) requirements of process performance yield. To solve this problem, multiple performance features need to be aggregated into a single index (Multi-Performance Characteristic Index) which can finally be optimized by any optimization algorithm/technique within search domain (domain of process variables).

In recent years, application of evolutionary techniques have come into picture to efficiently solve optimization problems in various fields such as industrial planning, scheduling, decision making and pattern recognition etc. These methods are based on nature based optimization ideology. The most common evolutionary method is genetic algorithm (GA) which is based on principles of genetics and evolution, and mimics the reproduction behavior observed in biological populations. Particle swarm optimization (PSO) technique is a heuristic technique which is basically inspired by social behavior of animals such as fish schooling or birds flocking; whereas, ant colony optimization (ACO) is motivated by foraging behavior of real life ant colonies. Applications of aforesaid algorithms have been well documented in literature (Malik et al. 2011; Pandu et al., 2013; Sait, 2010; Vijayakumar et al., 2003). Apart from GA, PSO and ACO, Harmony Search (HS) algorithm has been found quite new and efficient which is inspired by the improvisation process of musicians (Yang, 2009). Extensive applications of evolutionary techniques could be found in literature. For example, Hybrid Taguchi-Harmony Search algorithm for solving engineering optimization problems (Yildiz, 2008), hybrid immune algorithm for global optimization in design and manufacturing (Yildiz, 2009), hybrid immune-simulated annealing algorithm for optimal design and manufacturing (Yildiz, 2009b), hybrid immune-hill climbing optimization approach for solving design and manufacturing optimization problems in industry (Yildiz, 2009c), particle swarm optimization approach for product design and manufacturing (Yildiz, 2009d), new design optimization framework based on immune algorithm and Taguchi method (Yildiz, 2009e), structural design optimization of vehicle components using cuckoo search algorithm (Durgun and Yildiz, 2012), hybrid particle swarm optimization approach for structural design optimization in automotive industry (Yildiz, 2012), multi-objective optimization of vehicle crashworthiness using particle swarm based approach (Yildiz and Solanki, 2012), hybrid Taguchi-differential evolution algorithm for optimization of multi pass turning operations (Yildiz, 2013a), hybrid bee colony optimization approach for robust optimal design and manufacturing (Yildiz, 2013b), cuckoo search algorithm for the selection of optimal machining parameters in milling operations (Yildiz, 2013c), optimization of cutting parameters in multi-pass turning using artificial bee colony-based approach (Yildiz, 2013d), hybrid differential evolution algorithm for the selection of optimal machining parameters in milling operations (Yildiz, 2013e).

In this context, Harmony search (HS) algorithm, proposed by (Geem et al., 2001), is relatively new and inspired by the improvisation process of musicians. Literature depicts that HS algorithm has been widely used in process optimization. However, hardly evolutionary techniques are used to optimize process parameters for machining of composite materials in spite of tremendous scope exists in this direction. Since classical optimization methods are mostly single point gradient-based search techniques, they cannot explore the optimization landscape effectively. However, such limitations can easily be overcome by application of evolutionary algorithms.

It has been found that lesser extent of work has been carried out to optimize process parameters for machining of composite materials using evolutionary techniques. Hence, this work highlights application of harmony search (HS) algorithm to evaluate optimal machining condition in drilling of CFRP (epoxy) composites. In this work, drilling performance characteristics: thrust, torque and delamination factor (entry and exit both) have been clubbed into a single characteristic index i.e. MPCI (Multi-Performance Characteristic Index) by exploration of a Fuzzy Inference System (FIS). The advantage of using FIS is that it explores a logical rule base to understand input-output relationships and converts multiple inputs into single output. Moreover, in aggregating multiple inputs (drilling performance features, in the present case) assignment of response priority weight is not required. Apart from FIS, other aggregation approaches available in literature like utility theory, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and desirability function need response priority weights to be assigned. Assignment of priority weight depends on the decision-makers' discretion i.e. may vary from person to person. This may create uncertainty in decision making. The MPCI values (obtained from FIS) have been utilized to represent a nonlinear regression model in which MPCI has been explained as a function of drilling process parameters. The regression model has been treated as fitness function and finally optimized through HS algorithm. To show effectiveness of the proposed fuzzy embedded HS approach, the results have been compared with fuzzy based GA as well as Taguchi's robust optimization philosophy.

2.2.3 Experimentation

The drilling experiments have been conducted on MAXMILL 3 axis CNC machine with FANUC Oi Mate MC Controller (Model No. CNC 2000EG) as shown in Fig. 2.14. MAXMILL is a numerically controlled tool which performs drilling, parting, boring, roughing, chamfering and tapping using CNC programming and operating software. TiAlN coated solid carbide drill bit

(Manufacturer: WIDIA-Hanita) of different drill diameter such as 5 mm, 6 mm, 8 mm and 10 mm has been utilized for performing drilling operations (Fig. 2.15). Drill specifications have been given in Table 2.12. Values of thrust and torque have been measured using digital drilling tool dynamometer (Model No. MLB-DTM-DI-3; Make: MEDILAB ENTERPRISES, Chandigarh, INDIA). CFRP (polyester) composite plates (10 mm thickness) supplied by Samtech Engg. & Co. (P) Ltd., Ghaziabad, UP, India) have been used as work piece material (Fig. 2.16). The specification of work piece material has been furnished in Table 2.13. The conventional process parameters such as drill speed, feed and drill diameter have been considered in this experimental work. Aforementioned parameters have been varied into four discrete levels (Table 2.14). The experiments have been carried out according to Taguchi's L_{16} orthogonal array experimental layout (Table 2.15). During drilling operation on FRP composites, delamination is considered as one of the damaged modes observed in the drilled work pieces. Delamination generally reduces the component assembly tolerances and bearing strength. In this experimentation, delamination factor has been assessed to determine the level of delamination damage around the drilled holes. Delamination factor can be defined as the ratio of damaged area to the normal area around the drilled hole. Delamination factor (F_d) is computed using Eq. 1 shown below (Fig. 2.17).

$$F_d = {D_{max}}/{D} \qquad (2.17)$$

Here, F_d = delamination factor, D_{max} = maximum diameter observed in the damaged zone, D = diameter of the drilled hole (in ideal case this equals to the drill diameter). The pictorial views of the drilled holes have been captured using optical microscope (RADIAL INSTRUMENT with camera 30-X magnification). The delamination factor has been evaluated through image processing technique in MATLAB 13. The maximum diameter observed in the damaged zone has been measured in terms of pixelated region. Experimental data have been furnished in Table 2.16.

2.2.4 Fuzzy Inference System (FIS)

A Fuzzy Inference System (FIS) is a precise problem-solving methodology based on human inexact reasoning to handle numerical data and linguistic knowledge simultaneously (Cox 1992; Syung 2010; Abhishek et al. 2013). It has been widely applied in fields such as automatic control, data classification, decision analysis, expert systems and computer vision. A fuzzy inference system consists of four parts:

1. Fuzzification
2. Knowledge base
3. Inference engine and
4. Defuzzification.

Fuzzification: The real world input to the fuzzy system is applied to the fuzzifier. The purpose of fuzzification is to map the inputs from a set of sensors to values from 0 to 1 using a set of input membership functions

Knowledge base: The main part of the fuzzy system is the knowledge base in which both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules; whereas, the rule base contains a number of fuzzy IF-THEN rules.

Inference engine: The inference system or the decision making input performs the inference operations on the rules. It handles the way in which the rules are combined.

Defuzzification: The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to the crisp or in the form of real world input. The main function of defuzzifier is to convert fuzzy input to real world output.
The basic structure of FIS is shown in the following diagram (Fig. 2.18).

2.2.5 Nonlinear Regression

Nonlinear regression equation has been used to establish relationship between the dependent variable and a set of independent variable. In contrast to traditional linear regression which is constrained to estimating linear models, nonlinear regression can estimate models with arbitrary relationships between independent and dependent variables. The proposed mathematical model for response Y has been represented as below:

$$Y = C \times N^{a} \times f^{b} \times d^{c} \tag{2.18}$$

Here, C represents the constant; N represents spindle speed; f represents feed; d is the drill diameter. a , b , c are estimated coefficients of the said regression model.

2.2.6 Harmony Search (HS) Algorithm

Geem et al. (2001) proposed a meta-heuristic optimization algorithm inspired by the improvisation process of musicians. This algorithm utilizes the concept of developing a perfect state of harmony by improvising musical process such as during jazz improvisation. Here, this work is focused to optimize the drilling parameters by generating the perfect quality of music combination by adjusting the bandwidth, pitch and the best harmony memory to obtain global optimal solution (Geem et al. 2001; Manjarres et al. 2013; Lee and Geem 2005; Yang 2009; Omran and Mahdavi 2008). In this algorithm, the well trained musicians play music by generating New Harmony. When a musician plays music, he or she may play a pitch of her or his memory, creating music by adjusting the pitch rate randomly and playing new notes (Mahdavi et al. 2007; Omran and Mahdavi 2008). There are three main components i.e. harmony memory, pitch and randomization of notes which need to be formalized (Mahdavi et al. 2007; El-Abd 2013; Abhishek et al. 2014; Saka 2009; Chatterjee et al. 2014). In the HS algorithm, pitches of musical instruments are referred to the variables; whereas, solution is considered as harmony vector. This algorithm produces the aesthetic harmony which stores the best fitness value of the objective function in its memory. The process continues until the worst harmony is replaced with best harmony by adjusting of pitch and bandwidth continuously.
Followings are the steps involved in HS algorithm (Fig. 2.19).

I. **Initialization of the algorithm**

Interpret the objective function to be minimized as

f(y) subjected to $y_i \in Y_i$, i=1,2,….N (2.19)

where, y_i = set of decision variables

N = no. of decision variables

Y_i = possible range of values for each decision variable i.e. i.e. $_Ly_i \leq Y_i \leq {_Uy_i}$, and $_LY_i$ and $_Uy_i$ are the lower and upper bounds for each variable.

In HS algorithm, parameters such as harmony memory size (HMS), pitch adjusting rate (PAR), harmony memory considering rate (HMCR) bw (arbitrary distance band width) and stopping criterion (maximum number of iterations) are initialized first.

II. **Initiating the harmony memory**

Randomly generate vectors to fill the HMS matrix as solution vectors

$$HM = \begin{bmatrix} y_1^1 & y_2^1 & \cdots & y_n^1 \\ y_1^2 & y_2^2 & \cdots & y_n^2 \\ \vdots & \vdots & \vdots & \vdots \\ y_1^{HMS} & y_2^{HMS} & \cdots & y_n^{HMS} \end{bmatrix} \tag{2.20}$$

III. **Improvisation of new harmony:**

A new harmony vector, $y' = (y'_1, y'_2, \ldots, y'_i)$ is generate based on three rules: (1) memory consideration, (2) pitch adjustment and (3) random selection. Generating a new harmony is called improvisation. In the memory consideration, the value of the first decision variable y' for the new vector is chosen from any of the values in the specified harmony memory (HM) range $y' = (y - \acute{y}_1^{'HMS})$ Values of other decision variables $y' = (y'_1, y'_2, \ldots, y'_N)$ are chosen in the same manner. The HMCR, which varies between 0 and 1, is the rate of choosing one values from the historical values stored in the HM while (1-HMCR) is the rate of randomly selecting one value from the possible range of values.

$$y' \rightarrow \begin{matrix} y' \in \{y_i^1, y_i^2, \ldots, y_i^{HMS}\} & \text{with probability} = HMCR \\ y' \in Y_i & \text{with probability} = (1 - HMCR) \end{matrix} \tag{2.21}$$

Every component obtained by the memory consideration is examined to determine whether it should be pitch adjusted. This operation uses the PAR parameter, which is the art of pitch adjustment as follows:

Pitch adjusting decision for y' is given as:

$$y' \leftarrow \begin{cases} \text{Yes} & \text{for probability PAR} \\ \text{No} & \text{for probability } (PAR - 1) \end{cases} \tag{2.22}$$

Here, for the value of (PAR-1) sets no modification is done in y' and if the pitch adjustment decision is yes then modification is done as:

$$y' = y' \pm rand() \times bw \tag{2.23}$$

where, bw = arbitrary distance band width

$rand()$ = random number varies between 1 to 0.

In order to improve the global search capability of the HS algorithm, PAR and bw are dynamically adjusted with generation number. The PAR will be adjusted linearly as follows:

$$PAR(gnr) = PAR_{min} + \frac{PAR_{max} - PAR_{min}}{NI} \times gnr \tag{2.24}$$

Where, PAR (gnr) = the pitch adjustment rate for each generation,

NI = Number of solution vectors generations (iterations performed in the algorithm),

gnr = generation number

PAR_{min} and PAR_{max} minimum and maximum pitch adjustment rate.

Value of bw is decreased exponentially. Higher value of bw maximize the diversity of the solutions and lower the value of bw helps to tune the final solution.

$$bw(gnr) = bw_{max} \times e^{(c \times gnr)} \tag{2.25}$$

$$c = \frac{\ln\left(\frac{bw_{min}}{bw_{max}}\right)}{NI} \tag{2.26}$$

where bw(gnr) is the bandwidth for each generation, bw_{min} and bw_{max} are minimum and maximum bandwidth respectively.

IV. **Updating the new harmony:**

If new Harmony $y' = (y'_1, y'_2, \ldots, y'_N)$ is better than previous memory in the HM which can be judged in terms of objective function value (fitness function value), then the previous harmony (worst harmony) is replaced by new Harmony in existing HM.

V. **Stopping criteria**

Repeat Steps III and IV until maximum number of improvisations (stopping criterion) are reached, then stop.

2.2.7 Results and Discussions

2.2.7.1 Effect of Process Parameters on Output Responses

In the present study, attempts have been to investigate the effects of process parameters (drill rotational speed, feed and drill diameter) on machining performance characteristics like thrust, torque, delamination factor (both at entry and exit). ANOVA has also been performed to investigate the degree of significance of the drilling process parameters (Table 2.17a-2.17d).

2.2.7.2 Conversion of Multi-Responses into a Single Response

For multi-objective optimization, it is necessary to aggregate multiple responses into an equivalent single index. By this way, a multi-objective optimization problem can be transformed into a single objective optimization problem. However, such aggregation procedure must be logical. In this work, a Fuzzy Inference System (FIS) has been used to convert multiple responses into a single equivalent response. Initially, all the multi-output responses namely, thrust, torque and delamination factor (both at entry and exit) have been normalized (Table 2.18) and to convert them into a common dimensionless scale i.e. 0 to 1. Aforementioned response characteristics have been normalized by using following equation:

(Lower-is-Better, LB criterion): $$x_i^*(k) = \frac{\min x_i(k)}{x_i(k)} \qquad (2.27)$$

$i = 1, 2, 3, \ldots\ldots\ldots, n; \quad k = 1, 2, 3, \ldots\ldots\ldots\ldots, n$

$x_i^*(k)$ is normalized value for corresponding $x_i(k)$ experimental value.

In FIS, the aforementioned individual normalized multi-response characteristics have been considered as input variables. The output of this fuzzy inference system has been denoted as MPCI ((Multi-Performance Characteristic Index). Higher- is- Better (HB) criterion has been considered for optimizing (maximizing) the MPCI.

In order to evaluate MPCI, various membership functions have been assigned to each of the four output variables (Fig. 2.20). Here, the trapezoidal membership function has been assigned to convert crisp inputs into fuzzy data. In this FIS, each input and output i.e. MPCI has been expressed by three linguistic terms viz. "Low (L)", "Medium (M)", and "High (H) (Figs. 2.21-2.23). A set of 81 rules have been constructed (Figs. 2.26-2.27) and Table 2.19. Fuzzy logic converts linguistic inputs into linguistic output. Linguistic output has again been converted into numeric values (MPCI) by defuzzification method. Highest value of MPCI has been preferred.

2.2.7.3 Development of the Regression Model (Fitness Function)

Nonlinear regression model for MPCI has been developed by using SYSTAT 7 software. In the present work, Gauss-Newton algorithm has been used to generate the coefficients.

The mathematical model derived for MPCI has been given as follows:

For MPCI (CFRP 45^0 Fiber Orientations):

$$MPCI = 0.382 \times N^{-0.107} \times f^{0.281} \times d^{-0.227}$$

R^2= 99.6% (2.28a)

For MPCI (CFRP 90^0 Fiber Orientations):

$$MPCI = 0.471 \times N^{-0.172} \times f^{0.333} \times d^{-0.261}$$

R^2= 99.3% (2.28b)

The model adequacy has been tested by computing relative error:

$$\mathrm{Re}\,lative\ Error\ (\%) = \frac{|\text{Actual MPCI value - Predicted MPCI value}|}{\text{Actual MPCI value}}$$

The comparison between the actual MPCI and Predicted MPCI (derived from mathematical model) has been illustrated in Table 2.20. The %relative error has been found within 15% which is acceptable.

2.2.7.4 Optimization of the Fitness Function

The optimal process parameters in drilling of CFRP composites has been evaluated by using harmony search method. To show the effectiveness of aforesaid methodology, the results have been compared with genetic algorithm. The mathematical model derived for MPCI has been treated as the fitness function for the harmony search and genetic algorithm both. Initial tuning parameters setting for both the algorithms are described in Table 2.21. The results obtained from aforesaid algorithms have been furnished in Table 2.22. Figs. 2.28a, b (for CFRP 45^0 fiber orientation); Figs. 2.29a, b (for CFRP 90^0 fiber orientation); show convergence curve for HS and GA, respectively. It is to be noted that GA, HS provide optimal solution within the search domain (they follow continuous search, not discrete level of process parameters), however, as per availability of factorial/parametric setting in the experimental set up, the optimal setting may have to be altered to some extent. Because in most of the machines/set ups; factors can be varied at some discrete levels. In this context, application feasibility of Taguchi method deserves mention. Taguchi method can search optimal setting within discrete domain of process parameters. Hence, Taguchi predicted optimal setting can easily be adjusted in the machine/set up. Table 2.22 provides optimal settings obtained through GA and HS (both for CFRP plates 45^0 and 90^0 fiber orientations). The near optimal settings obtained in GA are: {N=1003.079~1000 RPM; f=344.789~350 mm/min, d=5 mm}; for CFRP (45^0) and {N=1028~1000 RPM; f=349.5~350 mm/min, d=5 mm}; for CFRP (90^0). The near optimal settings obtained in HS are: {N=1019.600~1000 RPM; f=350 mm/min, d=5 mm}; for CFRP (45^0) and {N=1088~1000 RPM; f=349.5~350 mm/min, d=5 mm}; for CFRP (90^0). The near optimal setting obtained in both the cases appear same {N=1000 RPM; f=350 mm/min, d=5 mm}, in which N=1000 RPM and f=350 mm/min can easily be adjusted in the machine/set up and drill bit of 5 mm is also available (refer Table 2.14). In order to verify aforesaid near-optimal setting {N=1000 RPM; f=350 mm/min, d=5 mm}, Taguchi method has been attempted by exploring L_{16} orthogonal array (Table 2.15) as design of experiment and corresponding MPCI values obtained from FIS model (Table 2.20) for CFRP (45^0 and 90^0 both). Taguchi method converts MPCI values into corresponding Signal-to-Noise (S/N) ratio using Higher-the-Better (HB) criterion. Finally, optimal setting has been evaluated through S/N ratio plot (Figs. 2.30a, b). The optimal setting appears as {N=1000 RPM; f=350 mm/min, d=5 mm} for both the cases (CFRP 45^0 and 90^0); the same has been obtained through GA as well as HS. This optimal setting has been verified through confirmatory test; showed satisfactory results.

In the present example, the identified optimum condition or the optimum level of factors is {N=1000 RPM; f=350 mm/min, d=5 mm} for both the cases (CFRP 45^0 and 90^0)

$$\eta_{opt} = m + (m_{N1000} - m) + (m_{f350} - m) + (m_{d5} - m)$$

m denotes overall mean value of S/N ratio for MPCI

m_{N1000} denotes average S/N ratio at N =1000 RPM

m_{f350} denotes average S/N ratio at f =350 mm/min

m_{d5} denotes average S/N ratio at d = 5 mm

Thus, application feasibility of fuzzy based HS algorithm has been examined in comparison with fuzzy embedded GA as well as Taguchi method. However, the difference between fuzzy based GA/HS and Taguchi method is that for GA/HS a mathematical model of fitness function is essential; whereas, Taguchi's optimization philosophy does not explore any mathematical model. Taguchi method explores quadratic loss function and S/N ratio concepts towards optimizing an objective function within discrete domain of process parameters.

It is to be noted that weighted function causes trade off problem while optimizing the process variables using nature inspired algorithm. Therefore, multi-objective paradigm using pareto optimality, crowding distance and 68odelli approach has been proposed. However, the present work attempts to convert multiple objectives into an equivalent objective function based on Fuzzy Inference System (FIS). No weight assigned through human judgment has been used in developing the objective function to avoid the issue of trade off effect. Rather, FIS has been used as an aggregation strategy for converting multiple objectives into an equivalent objective. The methodology depends on fuzzy rule base instead of weight assigned to various objectives. The granularity of FIS improves when number of fuzzy functions increases for expressing inputs and outputs of the system. In this case, three fuzzy functions such as "Low (L)", "Medium (M)", and "High (H)'' have been used to express the four input and output (single equivalent response). All the functions used have been trapezoidal membership functions. To obtain the rule in FIS, the rule base is constructed as follows:

$$R_i : if\ x_1\ is\ \ A_{i1},\ x_2\ is\ A_{i2}, and\ \ x_s\ is\ A_{iM} ....Then, y_i\ is\ C_i,$$

For example:

$$R_i : if\ N - Thrust\ \ is\ \ L,\ N - Torque\ \ is\ \ L,\ N - F_{in}\ \ is\ L\ and\ \ N - F_{out}\ \ is\ L......Then, MPCI\ \ is\ \ L$$

and so on….

These rules are more practically and logically compatible rather than weight assigned to various input parameters. This is the standard procedure for calculating MPCI (Multi performance characteristic index). Finally, the relationship between MPCI and input parameters has been developed through a valid non-linear regression analysis. The objective function so developed has been used in harmony search (HS) algorithm to find out optimal process parameters. In practice, the practitioners are interested in single best setting for machining rather than choosing a setting out of some hundred points available in pareto front. To ease the process of finding out best setting the proposed methodology has been adopted. It is proved that HS algorithm happens to be a latest evolutionary approach for optimizing complex functions with due emphasis on exploration and exploitation capability. The algorithm has been compared with other competing algorithms on the basis of standard functions. It is found to be working satisfactorily. The major advantages of HS algorithm are fast convergence and less parameter to be adjusted in comparison to genetic algorithm (GA).

2.2.8 Concluding Remarks

The study proposes a fuzzy-embedded HS algorithm through a case experimental research in which optimization of multiple performance characteristics such as thrust, torque, delamination factor (both at entry and exit) for drilling of CFRP (polyester) composite plates has been carried out in order to obtain the most favorable process environment (optimal parametric combination). The contributions of the present work have been summarized as follows.

1. ANOVA has been performed to assess the effects of drilling process parameters on thrust, torque and delamination factor (at entry and exit both) of drilled CFRP product.
2. Fuzzy Inference System (FIS) has been adopted to convert multi-responses into a single response (objective value), called Multi-Performance Characteristic Index (MPCI).
3. A nonlinear regression model for MPCI has been developed and be treated as fitness function for final optimization through HS algorithm.
4. Effectiveness of the proposed HS algorithm has been compared to that of GA and Taguchi's optimization philosophy.
5. The proposed fuzzy-based HS algorithm can fruitfully be applied in other manufacturing/production processes for offline quality control of the process performance yields.

Fig 2.14: Experimental set up

Fig 2.15: Drill bits used during experimentation

Fig 2.16: Drilled CFRP specimens

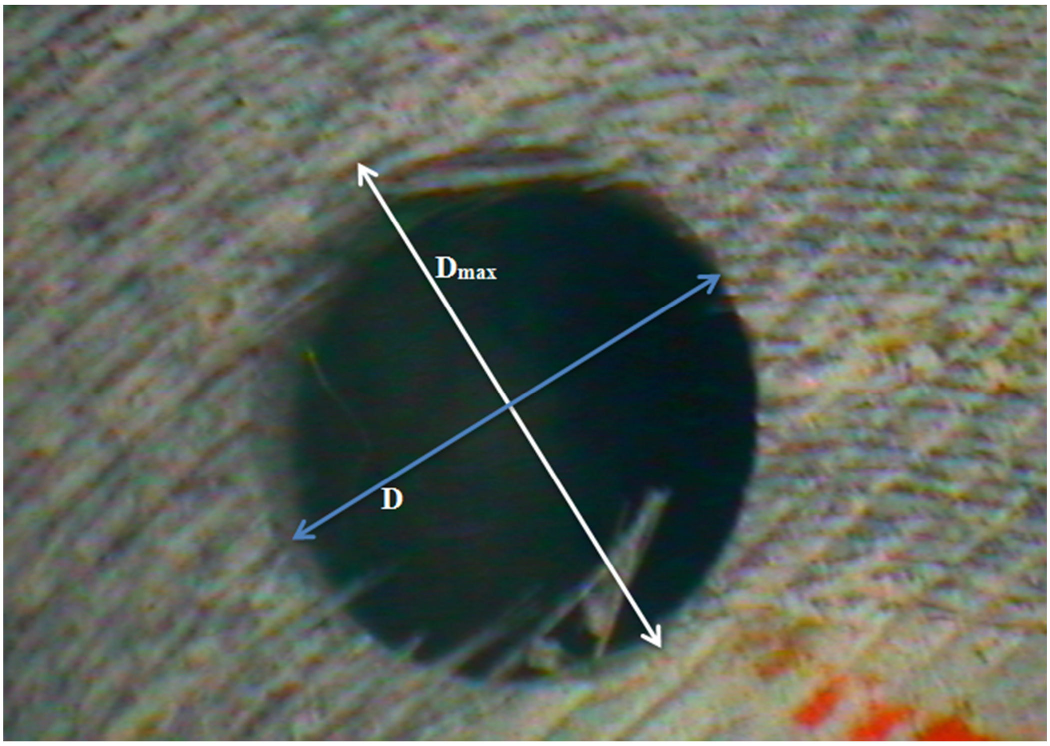


Fig. 2.17: Evaluation of delamination

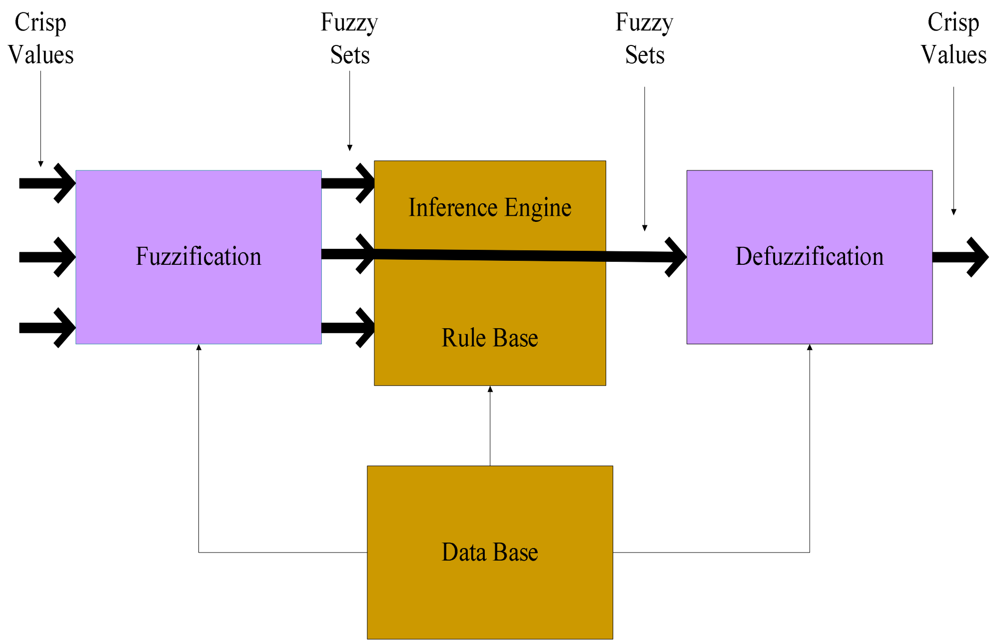


Fig. 2.18: Basic structure of Fuzzy Inference System (FIS)

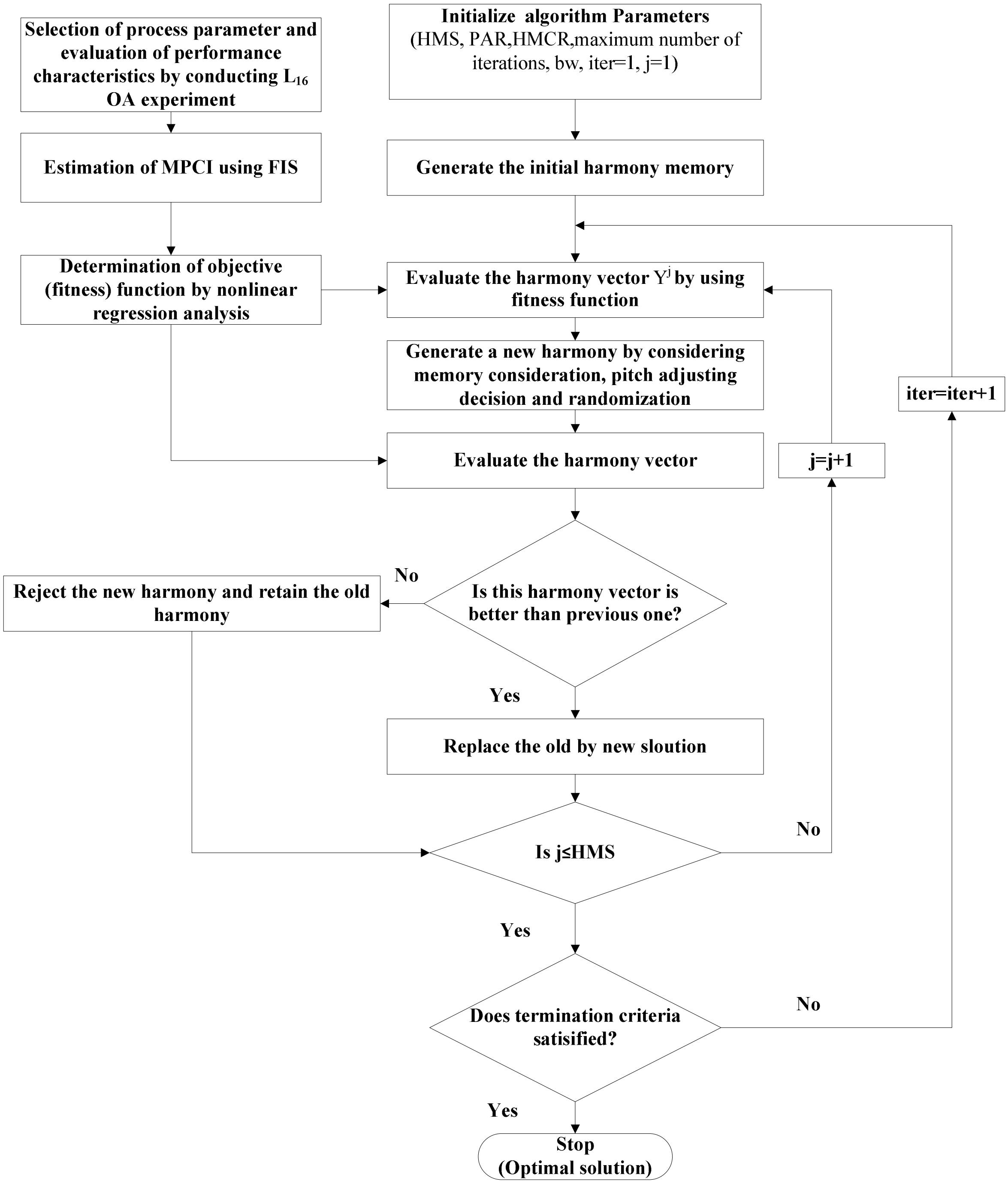


Fig. 2.19: Flow chart of the proposed methodology

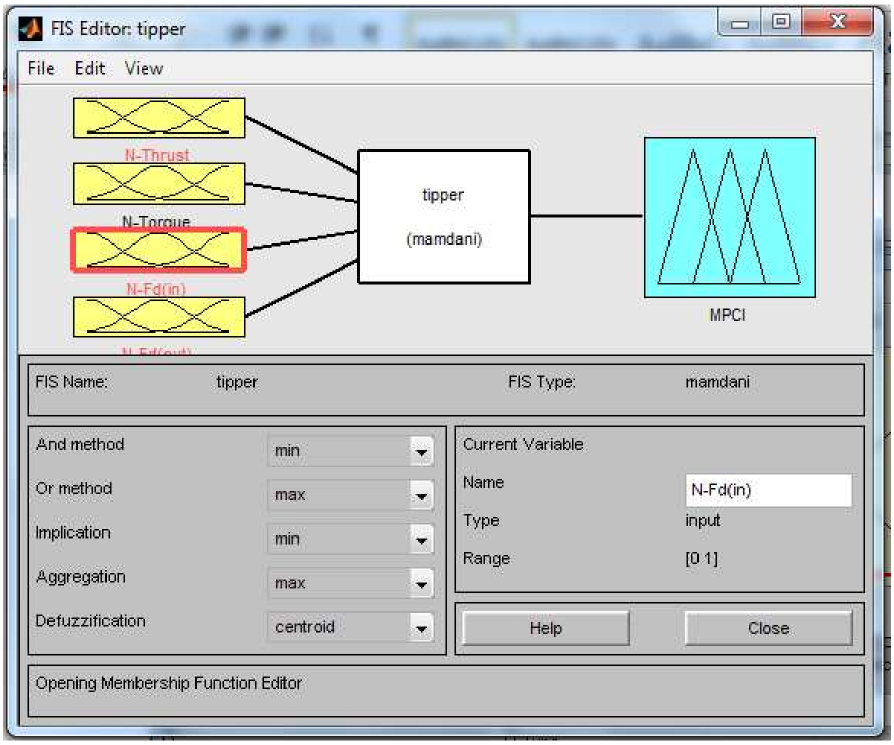


Fig. 2.20: Proposed FIS structure

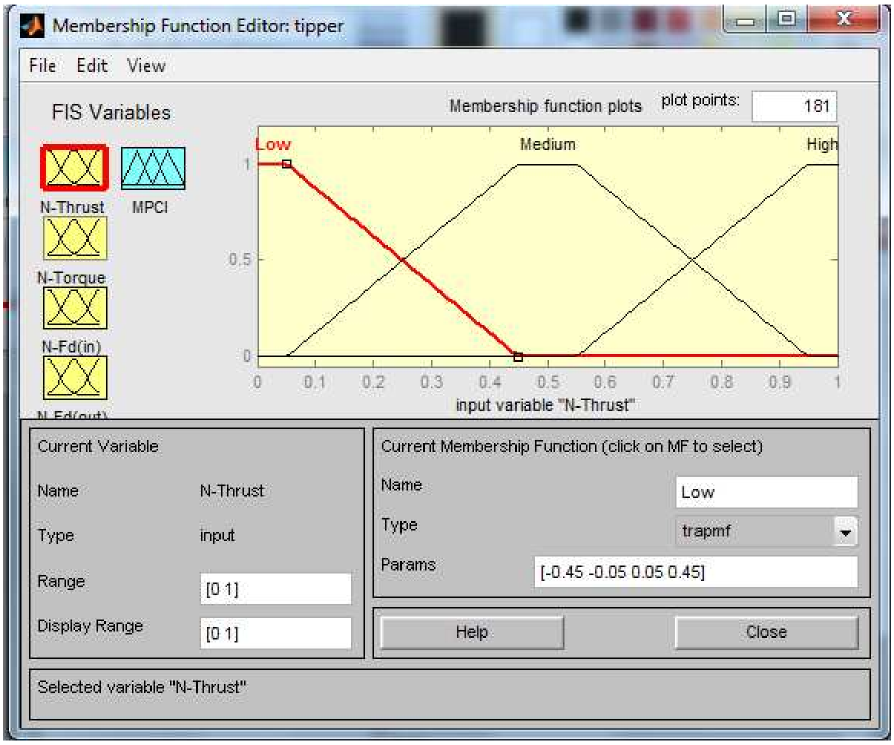


Fig. 2.21: Membership functions for N-Thrust

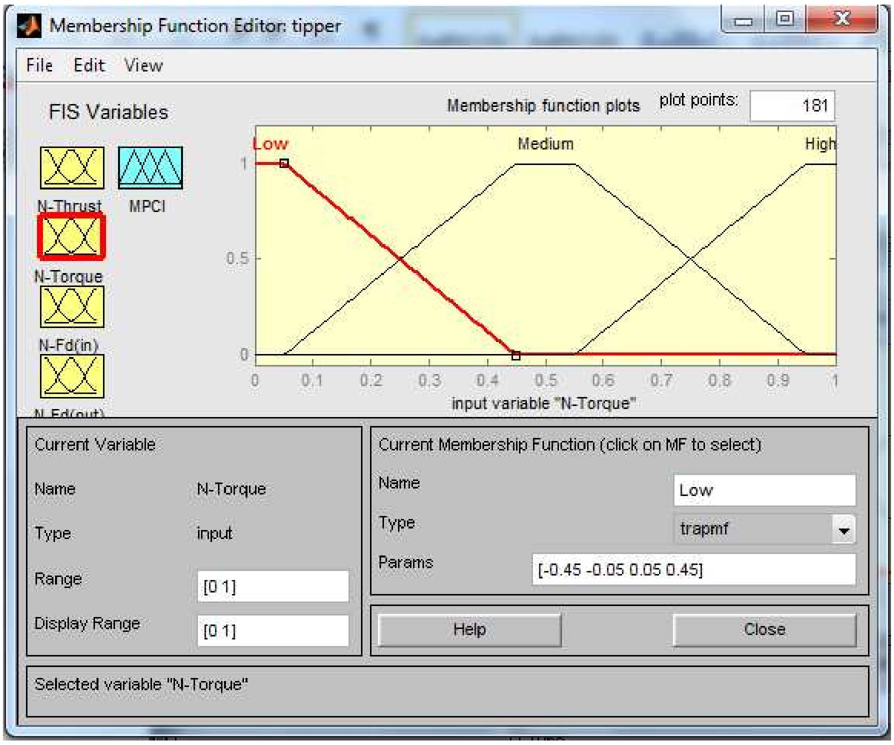


Fig. 2.22: Membership functions for N-Torque

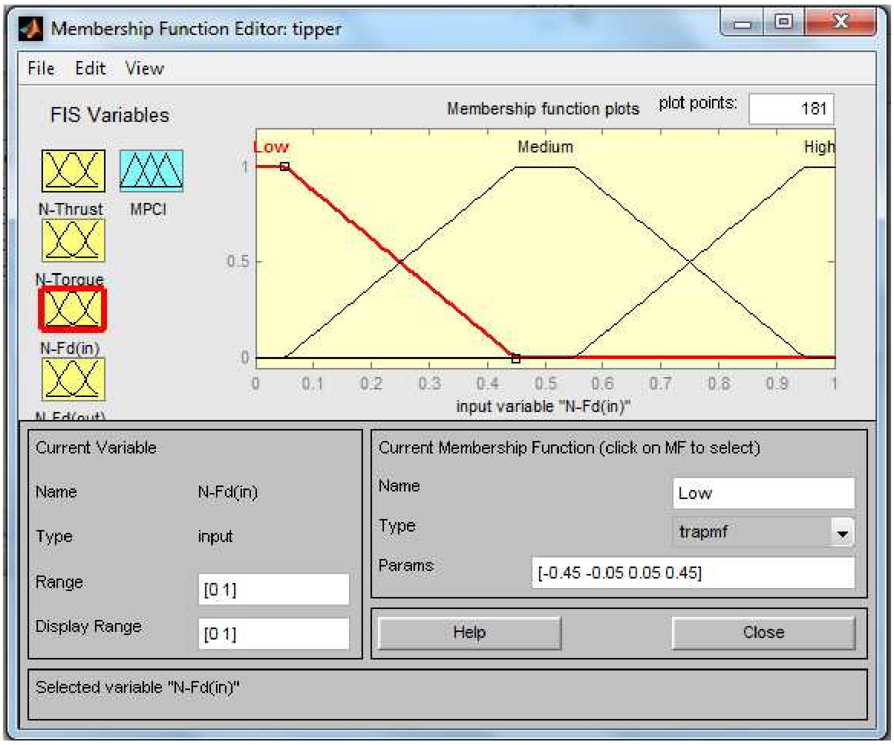


Fig. 2.23: Membership functions for N-F_d(in)

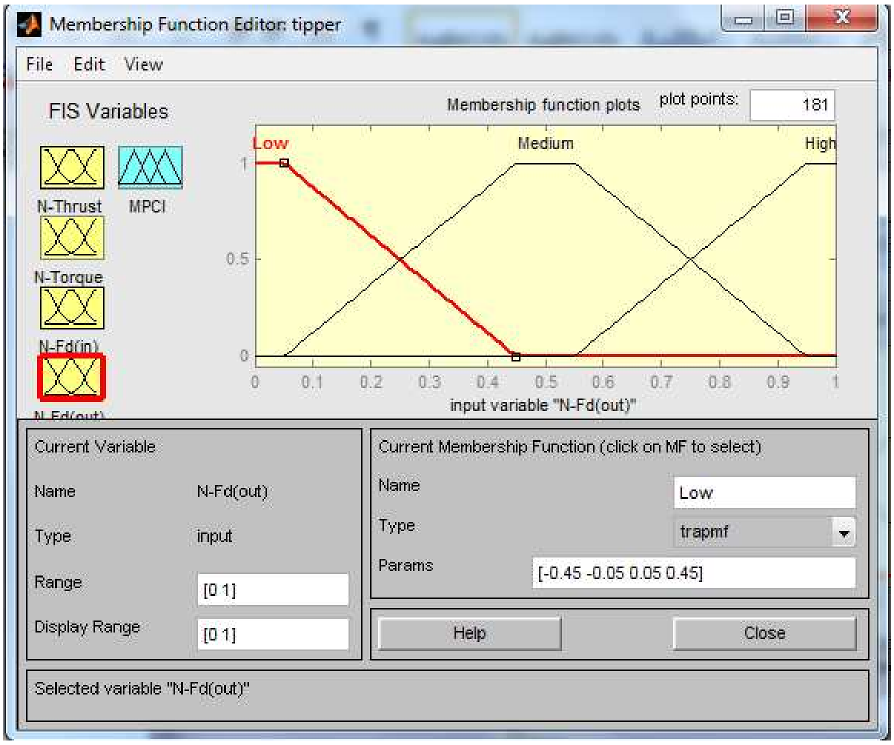


Fig. 2.24: Membership function for N-F_d(out)

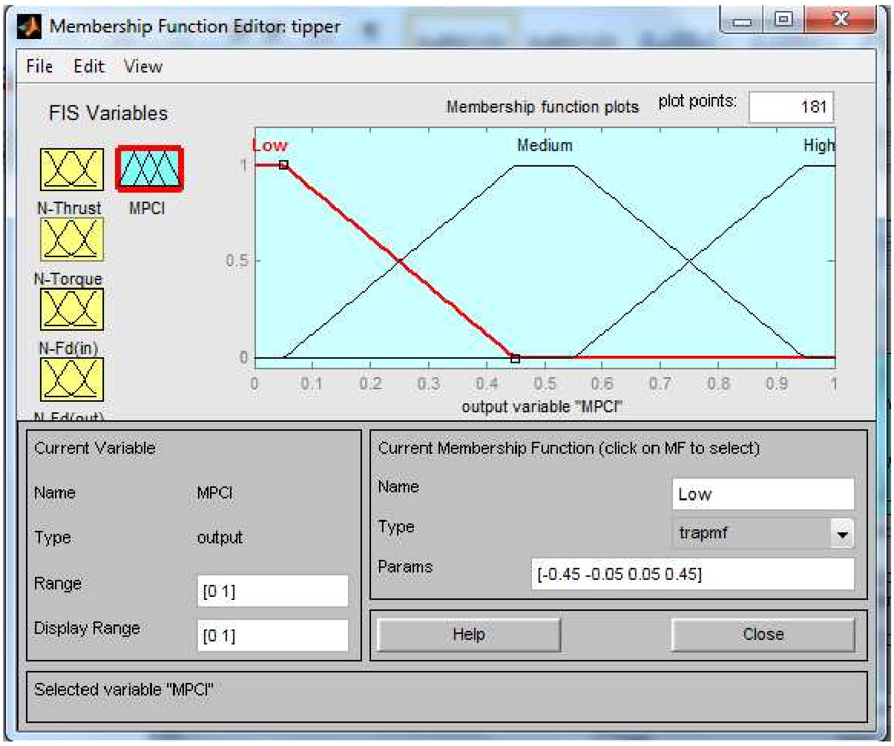


Fig. 2.25: Membership functions for MPCI

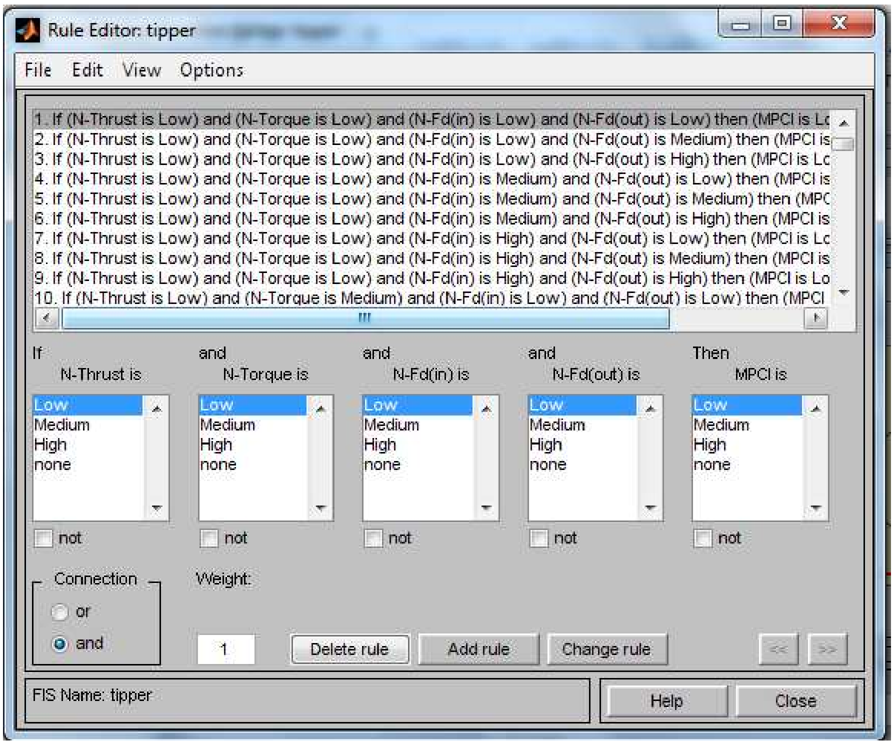


Fig. 2.26: Fuzzy rule editor

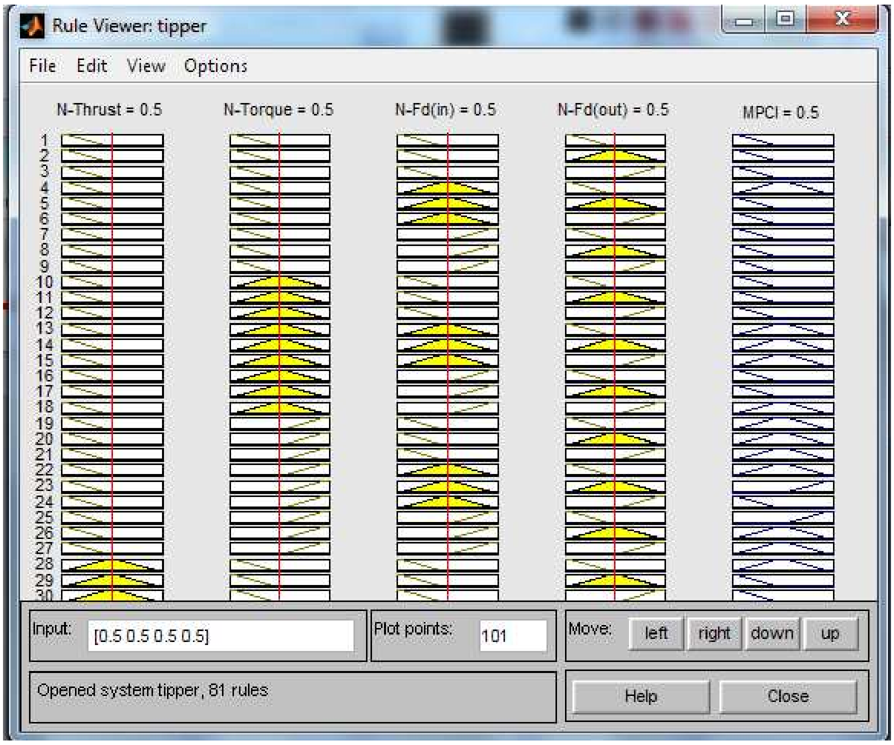


Fig. 2.27: Fuzzy rule viewer

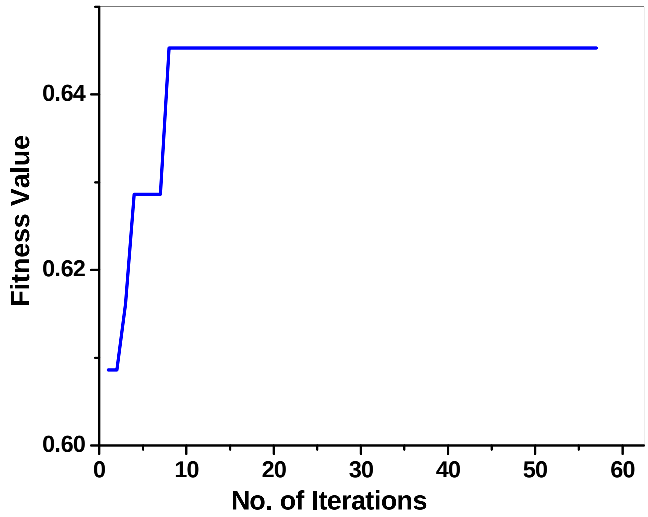


Fig. 2.28a: Convergence plot for MPCI by using Genetic Algorithm (CFRP 45^0)

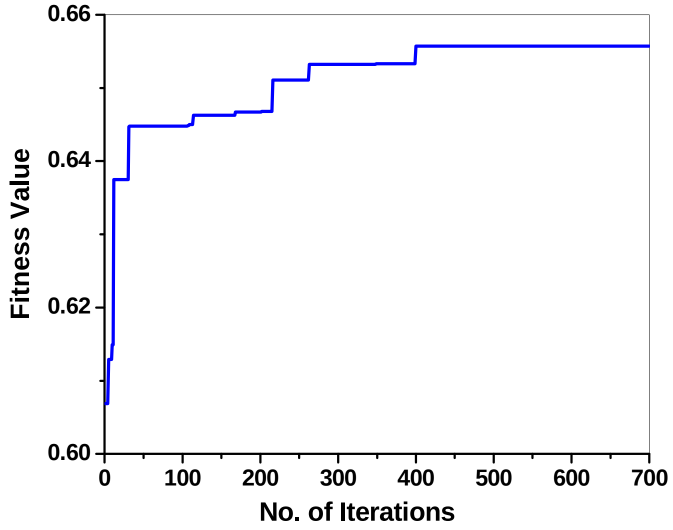


Fig. 2.28b: Convergence plot for MPCI by using Harmony Search (CFRP 45^0)

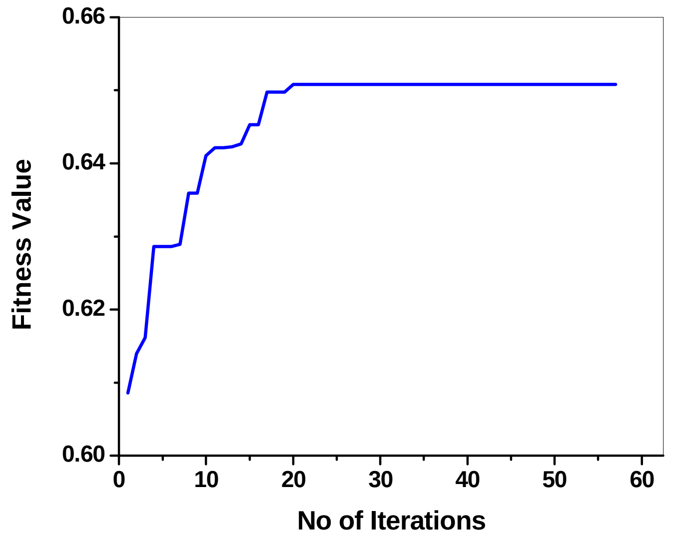


Fig. 2.29a: Convergence plot for MPCI by using Genetic Algorithm (CFRP 90^0)

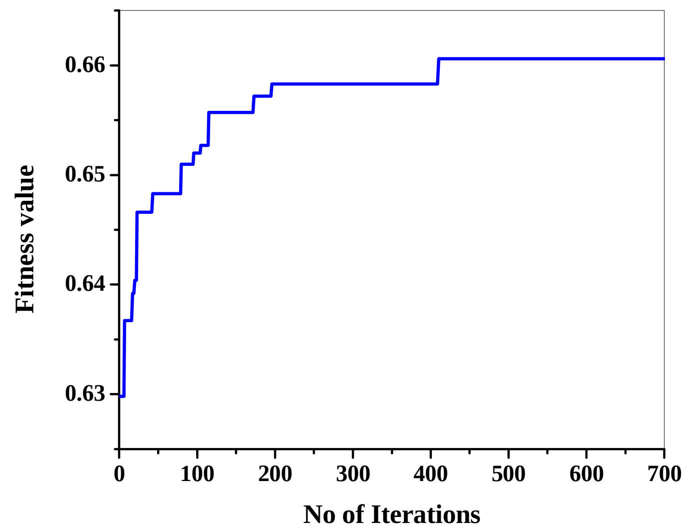


Fig. 2.29b: Convergence plot for MPCI by using Harmony Search (CFRP 90^0)

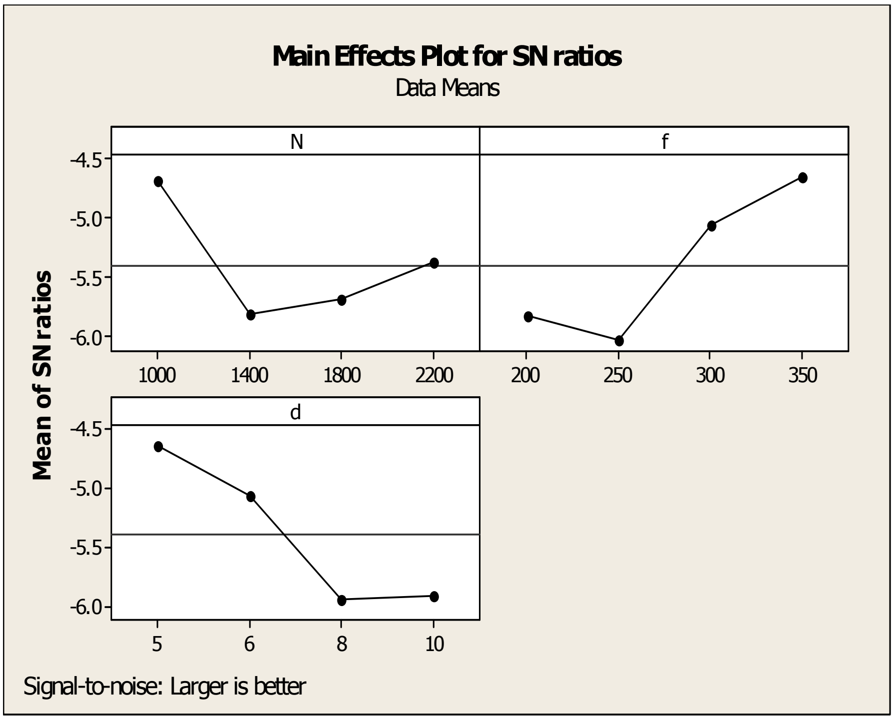


Fig. 2.30a: Main effect plot for MPCI (CFRP 45^0): Prediction of optimal setting by Taguchi method

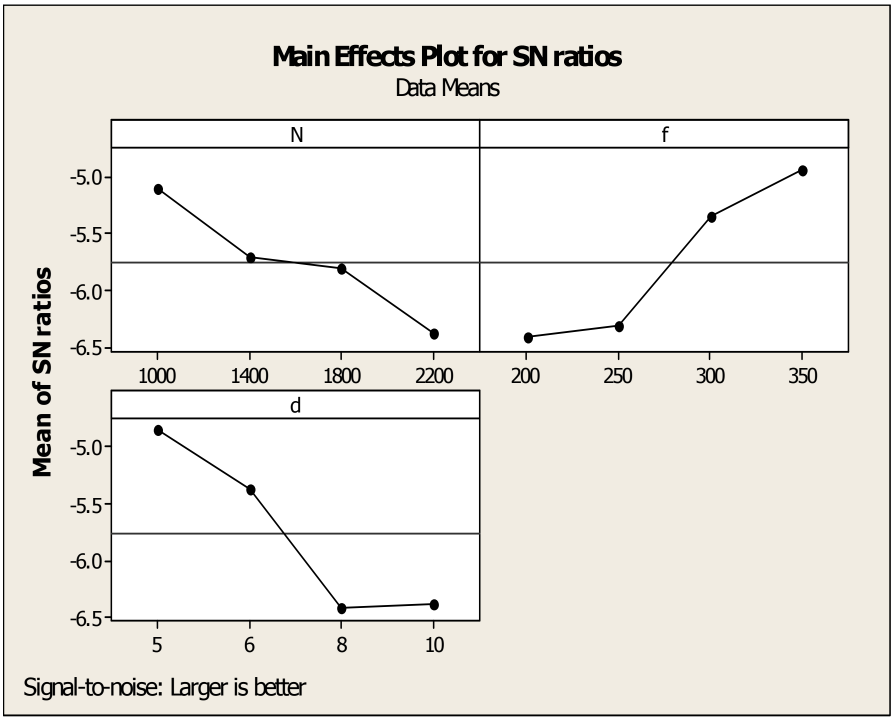


Fig. 2.30b: Main effect plot for MPCI (CFRP 90^0): Prediction of optimal setting by Taguchi method

Table 2.12: Specification of drills used in the experiments

Items	Specification/description
Product	M1308000RT
Shank Type	Plain
Overall Length (mm)	79.000
Shank Length (mm)	42.000
Drill Depth (mm)	27.000
Flute Length (mm)	37.000
Shank Size (mm)	8.000
Material	Solid Carbide
Point	118^0
Type	High Performance Drill
Number of Flutes	2
Drill Style	Metric
Coating	TiAlN

Table 2.13: Specification of CFRP plates

Specification/description	Value(s)
Density	02 gm/cm^3
Fibre orientations	$+90^0/-90^0$ and $+45^0/-45^0$
Fibre and matrix % ratio	resin: fibre = 70:30
Method of preparation	hand lay-up

Table 2.14: Domain of experiment (process parameters and their levels of variation)

Sl. No.	Process parameters	Notation	Unit	Level 1	Level 2	Level 3	Level 4
1	Drill Speed	N	[RPM]	1000	1400	1800	2200
2	Feed	f	[mm/min]	200	250	300	350
3	Drill diameter	d	[mm]	5	6	8	10

Table 2.15: Design of Experiment (DOE)

Sl. No.	L_{16} orthogonal array		
	N [RPM]	f [mm/min]	d [mm]
1	1000	200	5
2	1000	250	6
3	1000	300	8
4	1000	350	10
5	1400	200	6
6	1400	250	5
7	1400	300	10
8	1400	350	8
9	1800	200	8
10	1800	250	10
11	1800	300	5
12	1800	350	6
13	2200	200	10
14	2200	250	8
15	2200	300	6
16	2200	350	5

Table 2.16: Experimental data

Sl. No.	CFRP (Fibre orientation 45^0)				CFRP (Fibre orientation 90^0)			
	Thrust [kN]	Torque [kN-mm]	F_d(in)	F_d(out)	Thrust [kN]	Torque [kN-mm]	F_d(in)	F_d(out)
1	0.053	0.32	1.077	1.082	0.044	0.24	1.038	1.043
2	0.06	0.41	1.088	1.077	0.06	0.38	1.072	1.079
3	0.125	0.28	1.110	1.105	0.121	0.31	1.061	1.065
4	0.106	0.36	1.071	1.094	0.103	0.46	1.068	1.078
5	0.049	0.44	1.079	1.099	0.039	0.37	1.035	1.038
6	0.051	0.2	1.060	1.068	0.046	0.18	1.055	1.062
7	0.073	0.33	1.058	1.110	0.073	0.33	1.059	1.068
8	0.13	0.39	1.072	1.078	0.119	0.43	1.053	1.065
9	0.084	0.547	1.087	1.096	0.089	0.49	1.023	1.025
10	0.067	0.85	1.038	1.061	0.067	0.74	1.058	1.069
11	0.047	0.27	1.040	1.058	0.048	0.24	1.049	1.055
12	0.054	0.29	1.052	1.041	0.051	0.21	1.062	1.070
13	0.058	0.97	1.065	1.077	0.053	1.04	1.045	1.046
14	0.066	0.61	1.090	1.079	0.065	0.68	1.057	1.059
15	0.042	0.501	1.077	1.079	0.033	0.52	1.052	1.055
16	0.052	0.41	1.065	1.055	0.048	0.39	1.053	1.063

Table 2.17a: ANOVA for thrust and torque (Fibre orientation 45^0)

Source	DF	Seq SS		Adj MS		P-Value	
		Thrust	Torque	Thrust	Torque	Thrust	Torque
N	3	32.925	92.36	10.975	30.788	0.166	0.033#
f	3	4.737	19.49	1.579	6.496	0.794	0.377
d	3	69.559	76.01	23.186	25.338	0.044#	0.049#
Residual Error	6	27.359	31.61	4.560	5.269		
Total	15	134.580	219.48				

Table 2.17b: ANOVA for F_d(in) and F_d(out) (Fibre orientation 45^0)

Source	DF	Seq SS		Adj MS		P-Value	
		F_d(in)	F_d(out)	F_d(in)	F_d(out)	F_d(in)	F_d(out)
N	3	0.166	0.123	0.055	0.041	0.003#	0.042#
f	3	0.009	0.087	0.033	0.029	0.498	0.083
d	3	0.151	0.099	0.051	0.033	0.004#	0.065
Residual Error	6	0.021	0.047	0.003	0.008		
Total	15	0.348	0.356				

Table 2.17c: ANOVA for thrust and torque (Fibre orientation 90^0)

Source	DF	Seq SS		Adj MS		P-Value	
		Thrust	Torque	Thrust	Torque	Thrust	Torque
N	3	38.997	102.38	12.999	34.126	0.262	0.045#
f	3	5.646	25.63	1.882	8.544	0.859	0.372
d	3	87.794	101.88	29.265	33.960	0.074	0.046#
Residual Error	6	45.339	41.03	7.556	6.838		
Total	15	177.776	270.92				

Table 2.17d: ANOVA for F_d(in) and F_d(out) (Fibre orientation 90^0)

Source	DF	Seq SS		Adj MS		P-Value	
		F_d(in)	F_d(out)	F_d(in)	F_d(out)	F_d(in)	F_d(out)
N	3	0.017	0.032	0.006	0.011	0.636	0.552
f	3	0.043	0.052	0.014	0.017	0.302	0.370
d	3	0.044	0.049	0.015	0.016	0.295	0.397
Residual Error	6	0.057	0.083	0.009	0.014		
Total	15	0.161	0.217				

#Significant at 95% confidence level

Table 2.18: Normalized data [0, 1]

Sl. No.	(Fibre orientation 45^0)				(Fibre orientation 90^0)			
	N-Thrust	N-Torque	N-F_d(in)	N-F_d(out)	N-Thrust	N-Torque	N-F_d(in)	N-F_d(out)
1	0.792	0.625	0.964	0.962	0.750	0.750	0.986	0.983
2	0.700	0.488	0.954	0.966	0.550	0.474	0.954	0.950
3	0.336	0.714	0.935	0.942	0.273	0.581	0.965	0.963
4	0.396	0.556	0.969	0.952	0.320	0.391	0.958	0.951
5	0.857	0.455	0.962	0.947	0.846	0.486	0.989	0.987
6	0.824	1.000	0.980	0.975	0.717	1.000	0.970	0.966
7	0.575	0.606	0.981	0.938	0.452	0.545	0.967	0.960
8	0.323	0.513	0.968	0.966	0.277	0.419	0.972	0.962
9	0.500	0.366	0.955	0.949	0.371	0.367	1.000	1.000
10	0.627	0.235	1.000	0.981	0.493	0.243	0.967	0.959
11	0.894	0.741	0.998	0.984	0.688	0.750	0.975	0.972
12	0.778	0.690	0.987	1.000	0.647	0.857	0.964	0.959
13	0.724	0.206	0.975	0.967	0.623	0.173	0.979	0.980
14	0.636	0.328	0.953	0.965	0.508	0.265	0.968	0.968
15	1.000	0.399	0.964	0.964	1.000	0.346	0.973	0.972
16	0.808	0.488	0.975	0.987	0.688	0.462	0.972	0.964

'N-' means normalized

Table 2.19: Fuzzy rule matrix

Sl. No.	***IF &***	***IF &***	***IF &***	***IF &***	***THEN***
	N-Thrust	N-Torque	N- F_d(in)	N- F_d(out)	MPCI
1	L	L	L	L	L
2	L	L	L	M	L
3	L	L	L	H	L
4	L	L	M	L	M
5	L	L	M	M	L
6	L	L	M	H	L
7	L	L	H	L	L
8	L	L	H	M	L
9	L	L	H	H	L
10	L	M	L	L	L
11	L	M	L	M	L
12	L	M	L	H	L
13	L	M	M	L	M
14	L	M	M	M	M
15	L	M	M	H	M
16	L	M	H	L	L
17	L	M	H	M	L
18	L	M	H	H	M
19	L	H	L	L	M
20	L	H	L	M	M
21	L	H	L	H	M

22	L	H	M	L	M
23	L	H	M	M	H
24	L	H	M	H	L
25	L	H	H	L	H
26	L	H	H	M	M
27	L	H	H	H	M
28	M	L	L	L	M
29	M	L	L	M	L
30	M	L	L	H	L
31	M	L	M	L	L
32	M	L	M	M	L
33	M	L	M	H	M
34	M	L	H	L	M
35	M	L	H	M	M
36	M	L	H	H	L
37	M	M	L	L	L
38	M	M	L	M	M
39	M	M	L	H	M
40	M	M	M	L	M
41	M	M	M	M	M
42	M	M	M	H	M
43	M	M	H	L	M
44	M	M	H	M	M
45	M	M	H	H	M
46	M	H	L	L	M
47	M	H	L	M	L
48	M	H	L	H	M
49	M	H	M	L	M
50	M	H	M	M	L
51	M	H	M	H	M
52	M	H	H	L	M
53	M	H	H	M	H
54	M	H	H	H	H
55	H	L	L	L	M
56	H	L	L	M	M
57	H	L	L	H	L
58	H	L	M	L	L
59	H	L	M	M	H
60	H	L	M	H	L
61	H	L	H	L	L
62	H	L	H	M	M
63	H	L	H	H	M
64	H	M	L	L	M
65	H	M	L	M	M
66	H	M	L	H	M
67	H	M	M	L	L
68	H	M	M	M	L
69	H	M	M	H	M
70	H	M	H	L	M

71	H	M	H	M	H
72	H	M	H	H	H
73	H	H	L	L	M
74	H	H	L	M	M
75	H	H	L	H	M
76	H	H	M	L	H
77	H	H	M	M	L
78	H	H	M	H	H
79	H	H	H	L	H
80	H	H	H	M	M
81	H	H	H	H	M

Table 2.20: Evaluated MPCI and predicted MPCI

Sl. No.	(Fibre orientation 45^0)			(Fibre orientation 90^0)		
	MPCI (Obtained through FIS)	Predicted MPCI (Obtained through regression model)	Error (%)	MPCI (Obtained through FIS)	Predicted MPCI (Obtained through regression model)	Error (%)
1	0.608	0.561	7.725	0.576	0.551	4.410
2	0.546	0.573	4.967	0.5	0.566	13.101
3	0.551	0.565	2.561	0.507	0.557	9.948
4	0.632	0.561	11.238	0.652	0.554	15.092
5	0.501	0.519	3.643	0.487	0.495	1.743
6	0.535	0.576	7.703	0.6	0.560	6.714
7	0.511	0.518	1.409	0.5	0.496	0.735
8	0.500	0.569	13.852	0.493	0.554	12.333
9	0.481	0.474	1.555	0.481	0.440	8.482
10	0.436	0.479	9.922	0.42	0.447	6.507
11	0.582	0.590	1.445	0.576	0.570	1.112
12	0.596	0.592	0.747	0.593	0.572	3.587
13	0.465	0.441	5.254	0.385	0.401	4.209
14	0.488	0.493	1.117	0.434	0.458	5.546
15	0.593	0.554	6.502	0.584	0.525	10.155
16	0.622	0.603	2.982	0.54	0.579	7.269

Table 2.21: Initial parameter settings for HS and GA

Harmony Search Algorithm	Genetic Algorithm
Maximum No. of iterations = 700 harmony memory size = 6 harmony consideration rate (HMCR) = 0.9 minimum pitch adjusting rate (PARmin) = 0.4 maximum pitch adjusting rate (PARmax)= 0.9	Population size= 70 Maximum no. of generation= 100 Selection function= Stochastic function Elite Count= 2 Crossover fraction=0.8 Crossover function= Scattered Mutation factor=0.2 Mutation function= constraint dependent

Table 2.22: Optimal parametric combination (obtained by GA, HS algorithm and Taguchi method): Corresponding fitness function value(s)

Material	Algorithm/methodology	Optimal Parametric Combination			Fitness value (MPCI)
		Drill speed [RPM]	Feed [mm/min]	Drill diameter [mm]	
CFRP (45^0)	GA	1003.079	344.789	5	0.645
	HS	1019.600	350	5	0.653
	Taguchi Method	1000	350	5	0.6922
CFRP (90^0)	GA	1028	349.5	5	0.651
	HS	1088	349.5	5	0.6603
	Taguchi Method	1000	350	5	0.6777

2.3 Optimization of Thrust, Torque, Entry and Exit Delamination Factor during Drilling of CFRP (Epoxy) Composites: A PCA-Fuzzy-Taguchi Integrated Approach

2.3.1 Coverage

Amongst variety of fiber reinforced polymer (FRP) composites, the carbon fiber reinforced plastics (CFRP) are found highly promising materials for widespread applications in aeronautical and aerospace industries. The delamination is a major problem associated with drilling of fiber reinforced composite materials, which tends to reduce structural integrity of the said material. The problems in drilling, particularly the heterogeneity and anisotropy of composite materials increase delamination. Therefore, drilling of CFRP composites requires adequate attention towards achieving superior hole quality, surface finish as well as dimensional accuracy by achieving delamination free machining. However, drilling process is influenced by several machining parameters like: drill speed, drill bit diameter as well as drill material, feed etc. Direct and interactive effect of aforesaid process variables influences machining performance in terms of quality of the drilled hole. Therefore, an optimal parameter setting is indeed required.

To address these issues, present study aims at evaluating an appropriate drilling parameter setting towards optimization of thrust, torque, entry and exit delamination factor during drilling of CFRP (epoxy) composites. An integrated multi-response optimization philosophy combining Principal Component Analysis (PCA), Fuzzy Inference System (FIS) and Taguchi method has been proposed here. The aforesaid optimization module has been found efficient enough to overcome inherent limitations as well as unrealistic assumptions of existing optimization approaches as documented in literature so far.

2.3.2 Problem Definition

Machining of composite materials has appeared as an important topic for the researches; both in industry as well as academia. Determination of optimal cutting parameters is one of the most important elements in the machinability study of composites. Optimization has significant practical importance particularly for operating the machineries. In order to increase the accuracy of drill holes, the tool must be in good condition always as much as possible. To achieve satisfactory machining yields, the optimization of machining parameters like drill bit diameter, spindle speed, and feed rate are mandatory (Jayabal and Natarajan, 2010).

Literature depicts that extensive work has been performed so far by the pioneer researchers in modeling, simulation of machining aspects of CFRP composites. Aspects of delamination free drilling has been given vital importance as well as main research focus. Optimization of composite machining has been attempted; but to a limited extent. However, in the context of mass production, parametric optimization is utmost important to make a compromise balance between cost as well as quality. Drilling is a multi-factor multi-response machining operation characterized by several process parameters along with various output responses. Material Removal Rate (MRR), dimensional accuracy, surface finish are the major output parameters of concern. Composite drilling differs from conventional drilling of metals due to the phenomenon called delamination. Effort must be made to pursue delamination free drilling so as to achieve satisfactory machining performance. In this context, parametric optimization deservers mention.

Taguchi's optimization philosophy is the starting point for every manufacturing process/product optimization. However, this philosophy is being worldwide criticized due to its inability to solve multi-objective optimization problem. To get rid of this; literature highlights application of grey relational analysis (Datta et al., 2008), desirability function approach (Datta et al., 2011), utility theory (Deb Barma et al., 2012), TOPSIS (Singh et al., 2011), Fuzzy Inference System (Verma et al., 2011), Principal Component Analysis (PCA) (Roy et al., 2012), individually integrated with Taguchi method. The main motto is to convert multiple objectives into an equivalent single objective function; which can finally be optimized by Taguchi method. However, these approaches rely on some assumptions. Response correlation is being neglected in grey theory, desirability function, TOPSIS as well as utility theory. Moreover, assignment of response priority weight depends on the perception of the decision-makers (DMs). PCA has the capability in eliminating response correlation and to convert correlated multi-responses into uncorrelated indices called individual principal components (Singh et al., 2013). Individual principal components need to be aggregated to compute a composite principal component which is to be optimized finally by Taguchi method. Aggregation of individual principal components encounters consideration of response priority weights which is ambiguous and basically vague in nature (depends on expert opinion). In order to avoid this limitation, development of an integrated multi-objective optimization module is indeed necessary.

The present work proposes application of PCA-Fuzzy integrated with Taguchi's philosophy in a case application in drilling of CFRP composites. Spindle speed (rotational speed of the drill bit), feed and drill diameter has been considered as process input variables; while output parameters considered as: thrust, torque, entry and exit delamination factor (of the drilled hole). The research attempts to evaluate an optimal parameter setting to maximize machining performance.

2.3.3 Experimental Details

Drilling operations have been executed on CNC drilling machine [MAXMILL 3 axis CNC machine with FANUC Oi Mate MC Contoller, Model No. CNC 2000EG] (Fig. 2.14 of Section 2.2). MAXMILL is numerically controlled tool, used for machining parts featuring high speed, high accuracy and high productivity. It performs drilling, parting, boring, roughing, chamfering, tapping of circular and rectangular work-piece using CNC programming and operating software.

CFRP composite bars (50 mm diameter and 10 mm thickness; supplied by Samtech. Engg. & Co. (P) Ltd., Gaziabad UP) have been used as work piece material as shown in Figure 2.31. Relevant information of the said work piece material has been furnished below (Table 2.23).

TiAlN coated solid Carbide drill bit [Manufacturer: WIDIA-Hanita] of different size such as 6 mm, 8 mm, and 10 mm has been utilized for performing drilling operation. Drill specifications have been given in (Table 2.24).

Design of Experiment (DOE) has been selected as per mixed level L_{18} Orthogonal Array (Table 2.25). Drill speed [RPM], feed [mm/min] and drill diameter [mm] have been considered as controllable process parameters. Drill speed has been varied into six discrete levels; whereas, feed and drill diameter have been varied into three different levels (Table 2.26).

The experiments have been conducted as per run order shown in Table 2.25. The entire experimental scheme explored 2 replicates. That means for each parameter setting experiments have been conducted twice and the average data has been taken (Table 2.27). Same procedure has been adapted for the validation test also.

The purpose is to investigate effects of aforesaid process variables on multiple performance characteristics: thrust, torque, and entry delamination factor as well as exit delamination factor. Thrust and torque has been evaluated by using Digital Drilling Tool Dynamometer [Model No. MLB-DTM-DI-3; Make: MEDILAB ENTERPRISES, Chandigarh, INDIA]. The entry delamination factor and exit delamination factor has been assessed by the formula given below:

$$F_d = D_{\max}/D \qquad (2.29)$$

Here, F_d = delamination factor, $D_{\max}$ = maximum diameter observed in the damaged zone, D = diameter of the drill bit.

Pictorial representation showing inlet and outlet diameter of the drilled hole has been presented in Figs. 2.32a, b. Experimental data have been furnished in Table 2.27.

2.3.4 Optimization Methodology

In order to ensure satisfactory machining performance; optimization of thrust, toque, entry-exit delamination factor is necessary during machining of CFRP composites. A PCA-Fuzzy-Taguchi integrated optimization module has been adapted for the aforesaid purpose. This section provides basic preliminaries of the theoretical background, formulation of Principal Component Analysis (PCA), Fuzzy Inference System (FIS) and Taguchi method.

2.3.4.1 Principal Component Analysis (PCA)

PCA is a commendable statistical methodology to resolve the correlation problem amongst the responses. *Pearson in 1901* first came up with this methodology, and developed as a statistical tool by *Hotelling* in 1993 (Tong et al., 2005; Chakravorty et al., 2012).

PCA is a most useful methodology with benefits of simplifying a number of correlated variables into equal to less number of uncorrelated principal components conserving considerable original information by utilizing linear combination and considerably easing stowing. By anticipating the eigenvectors of the covariance matrix of the original inputs, the principal components are evaluated. The evaluated variables are ordered in accordance with their variance indicating an abbreviating importance in consideration of acquiring the complete information element of the original data set. The principal components can be utilized for the adequate illustration of the system under investigation as represented as linear combinations of the original variables and are orthogonal to each other. The data are normalized before evaluating the principal components, to maintain some variables or observations from extricating the calculations. Avoidance and elimination of the effects of the units and the relative spread of the data used for evaluating the multiple performance characteristics and effects of units can be achieved by such data preprocessing. An adequate of information for deciding the optimal levels of control parameters is accommodated by the normalization of data. The original data are translated values ranging from values 0 to 1 with 1 considering as the best performance and 0 as the worst (Tong et al., 2005; Datta et al., 2009).

The formula for normalization of Higher-is-Better (HB) characteristic is as follows:

$$x_i^*(j) = \frac{x_i(j) - [\min(x_i(j))]}{[\max(x_i(j)) - \min(x_i(j))]} \tag{2.30}$$

The normalization formula for Lower-is-Better (LB) criteria is:

$$x_i^*(j) = \frac{[\max(x_i(j))] - x_i(j)}{[\max(x_i(j)) - \min(x_i(j))]} \tag{2.31}$$

$X_i(j)$ is the value for the response for i^{th} experiment, $\min X_i(j)$ and $\max X_i(j)$ is the smallest and the largest value for $X_i(j)$.

The steps of PCA are described as follows:

1. Inspecting correlation among each pair of quality characteristics:

Let $Q_i = \{X_0^*(i), X_1^*(i), ..., X_m^*(i)\}$, where $i = 1,2,3.......n$ (2.32)

It is the normalized series of the i^{th} quality characteristic. The correlation coefficient among two quality characteristics is evaluated by the following equation:

$$\rho_{jk} = \frac{Cov(Q_j, Q_k)}{\sigma_{Q_j} \times \sigma_{Q_k}} \tag{2.33}$$

Here,

$j = 1,2............n$

$k = 1,2..........n$

$j \neq k$

Here, ρ_{jk} is the correlation coefficient, $\sigma_{Q_j}, \sigma_{Q_k}$ denotes standard deviation of the quality characteristics j and quality characteristics of k respectively.

2. Computation of the principal component score

a. Calculate the Eigen value λ_k and the corresponding Eigen vector $\beta_{kj}, k = (1,2,...,n)$ from the correlation matrix developed by all the quality characteristics.

b. Calculate the principal component scores of the comparative sequence and normalized reference sequence utilizing the equation shown below:

$$Y_i(k) = \sum_{j=1}^{n} x_i^*(j)\beta_{kj}, (i = 0,1,2,...,m); (k = 1,2,...,n.) \qquad (2.34)$$

Here, $Y_i(k)$ is the principal component score of the k^{th} element in the i^{th} series. $X_i^*(j)$ is the normalized value of the j^{th} element in the i^{th} sequence, and β_{kj} is the j^{th} element of the Eigen vector β_k.

3. Estimation of quality loss $\Delta_{0,i}(k)$

Loss estimate $\Delta_{0,i}(k)$ is defined as the absolute value of the difference between i^{th} experimental value for the k^{th} response and the desired (ideal) value. If responses are correlated then on the contrary of using $[X_0(k)X_i(K)]$; $[Y_0(k)Y_i(k)]$ should be utilized for calculation of $\Delta_{0,i}(k)$.

2.3.4.2 Fuzzy Inference System (FIS)

Fuzzy inference is the method in which the mapping from a given input to an output is formulated utilizing fuzzy logic. Then decisions can be drawn, or patterns discerned on the basis of mapping. Fuzzy logic can potentially acquire human decision making, commonsense reasoning, and other perspectives of human apprehension. The fuzzy-rule based methodology is a core reasoning process where expert experience and subject knowledge can possibly be implemented and translated into the machine language. The following elements involve the process of fuzzy inference: Membership Functions, IF-THEN Rules and Logical Operations (Horng and Chiang, 2008; Chiang and Chang, 2006).

Generally two kinds of fuzzy inference systems can be utilized: *Mamdani* type and *Sugeno* type. Depending on the way in which outputs are determined, these two types of inference systems are varied. The most commonly utilized fuzzy methodology is *Mamdani's* fuzzy inference method (Mamdani, 1976a; 1976b). *Mamdani* fuzzy model is developed on the basis of the combinations of IF-THEN rules taking account both consequent predicts and fuzzy antecedent. In this model, the rule base is usually developed by an expert and therefore, it is diaphanous to study and understand is the advantage of this model. Because of its ease implementation, for sorting out a numerous real world problems, *Mamdani* model is still most primarily utilized.

A fuzzy system generally consists of four components i.e. fuzzifier, an inference engine, a knowledge base and a defuzzifier. The membership functions are first utilized by fuzzifier to convert the crisp inputs into fuzzy sets. Then, the fuzzy values are generated by the action of inference engine on fuzzy rules performing fuzzy reasoning. After that the defuzzifier defuzzifies these fuzzy values into crisp outputs (Lin et al., 2002; Lin and Lin, 2005; Yilmaz et al., 2006). These four components are shown in Fig. 2.33.

The membership functions, which characterize the degree of participation of an object in a fuzzy set, evaluate the fuzzy values. Generally, trial and error methods are implemented for this. The *Mamdani* inference method based on fuzzy rules is utilized in this present study for fuzzy inference reasoning.

To develop a rule,

$R_i : If\ x_1\ is\ A_{i1}; x_2\ is\ A_{i2}\ \&\ x_s\ is\ A_{is}$

Then $y_i\ is\ C_i$.

Here, $X_j\,(j = 1,2,...,s)$ are the input variables, y_i are the output variables and A_{ij} and C_i are fuzzy sets designed by the membership functions $\mu_{A_{ij}}(x_j)$ and $\mu_{Ci}(y_i)$ respectively. M is the total number of fuzzy rules. The aggregated output for the M rules based on the *Mamdani* implication method is as follows:

$$\mu_{Ci}(y_i) = \max\{\min[\mu_{Ai1}(x_1), \mu_{Ai2}(x_2),..., \mu_{Ais}(x_s)]\}, i = 1,2,..., M. \qquad (2.35)$$

Then fuzzy set for each output variable requires defuzzification, after the aggregation process. Fuzzy values can be converted into one single crisp output value utilizing the defuzzification method. One of the well-known techniques *the centre of gravity method* is utilized for defuzzifying fuzzy output functions is used in this study. The formula to calculate the centroid of the combined output $\hat{y}_i$ is given by:

$$\hat{y}_i = \frac{\int y_i \mu_{Ci}(y_i)dy}{\int \mu_{Ci}(y_i)dy} \tag{2.36}$$

2.3.4.3 Taguchi Method

Taguchi method (originated by *Dr. Genichi Taguchi* in the late 1940's*)* is a popular robust design philosophy which enhances engineering productivity (Dean, 1992; Roy, 2001).

Designers can utilize standard and systematic approach for executing experimentation to obtain optimum settings of design parameters for quality and cost very efficiently. The method gives priority to move quality back to the design stage, pursuing to design a process/ product. Orthogonal arrays are utilized in course of Taguchi method, to analyze a large number of variables with a fewer number of experiments. The conclusions made from small-scale experiments are genuine over the complete experimental domain consists of the control factors and their corresponding level settings. This method can decrease the cost of advancement and research by investigating an enormous number of parameters simultaneously. The Taguchi method utilizes a statistical measure of performance called Signal-to-Noise (S/N ratio), in order to examine the results. The S/N ratio takes into account both the mean and the variability of the response data. After performing the statistical analysis of S/N ratio, an Analysis of Variance (ANOVA) requires to be applied for estimating the relative importance of various factors and for computing error variance. The predicted optimum setting need not correspond to one of the rows of the matrix experiment in Taguchi method for parameter design. Therefore, an experimental confirmation is run utilizing the predicted optimum levels for the process parameters being investigated. The intention is to confirm that the optimum conditions suggested by the matrix experiments do indeed contribute the projected improvement. If the projected improvements and observed match, the suggested optimum conditions will be adopted (Dean, 1992; Tsui, 2007).

Taguchi's S/N ratio for Performance Evaluation

There is a loss function which describes the deviation from the target (desired level) and further transformed into S/N ratio. The transformed S/N ratio is also defined as quality evaluation index. The least variation and the optimal design are obtained by analyzing S/N ratio. The higher the S/N ratio, the more stable the achievable quality. It also reduces the sensitivity of the system performance to source of variation (Tsui, 2007; Mahapatra and Patnaik, 2007).

There are three S/N ratios of common interest for optimization of static problems;

Nominal-the-Best (NB)/ Target-the-Best (TB): In this approach, the closer to the target value, the better and the deviation is quadratic. The formula for these characteristics is:

$$S/N = -10\log\frac{y}{S_y^2} \tag{2.37}$$

Lower-is-Better (LB): The Lower-is-Better (LB) approach held when a company desires smaller values. The formula for these characteristics is:

$$S/N = -10\log\frac{1}{n}\sum y^2 \tag{2.38}$$

Higher-is-Better (HB): Higher-is-Better (HB) is required when a manufacturer desires higher values of a characteristic. The formula for these characteristics is:

$$S/N = -10\log\frac{1}{n}\sum\frac{1}{y^2} \tag{2.39}$$

Here,

$y =$ Average of observed values;

$S_y^2 =$ Variance of y;

$N =$ Number of observations

However, Taguchi method is considered only for single objective optimization problems. It cannot be utilized for getting the single optimal setting of process parameters considering more than one performance parameter.

2.3.5 Results and Discussions

Experimental data (corresponding to Table 2.27) have been converted into corresponding S/N ratios using Taguchi's S/N ratio formula (LB) shown as follows:

Lower-is-Better (LB) criterion:

$$\eta_{ij} = -10\log\left(\frac{1}{n}\sum_{j=1}^{n} y_{ij}^2\right) \tag{2.40}$$

Here, y_{ij} is the i^{th} experimental result at the j^{th} test, n is the total number of the tests.

Computed S/N ratios have been furnished in Table 2.28. These S/N ratios have then been normalized (Table 2.29) based on Higher-is-Better (HB) criterion using the following equation:

$$y_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \quad (2.41)$$

After normalizing, a correlation test has been made to check whether responses are correlated or not. It has been found that correlation exists amongst responses. Correlation check results have been shown below (Table 2.30).

Individual principal components (three major PCs) need to be combined/ aggregated for further optimization using Taguchi method. As Taguchi method fails to solve multi-objective optimization problem; therefore, multiple objectives required to be aggregated to derive an equivalent single objective which can easily be optimized in Taguchi method.

Eigen values, Eigen vectors, accountability proportion (AP) and cumulative accountability proportion (CAP) computed in PCA for performance evaluation indicators (S/N ratios) has been shown in Table 2.31. It has been found that, the first three PCs can take care of 46.3%, 32.7% and 13.0% data variability respectively. The contribution of fourth has been found negligible effect to interpret data variability. Consequently, effects of the 4th PC have been found negligible and the first three PCs have been considered for further analysis (Table 2.32).

The paper highlights two different aggregation philosophies in order to combine individual PCs to compute a single objective.

1. The concept of Multi-Performance Characteristic Index (MPCI) [Singh et al., 2013], and secondly,
2. The concept of Normalized Combined Quality Loss (NCQL)

Block diagram of the proposed optimization module (two approaches) has been provided in the (Fig. 2.44).

In the first approach, individual PCs (PC1, PC2 and PC3) have been normalized (Table 2.33) and fed as inputs to the Fuzzy Inference System (FIS) engine which could combine multi-inputs into a single characteristic output (MPCI) (Fig. 2.34). For assessing MPCI in fuzzy inference system (FIS), the membership functions for the input process variables such as (normalized) PC1, PC2 and PC3 has been defined as ‘Small’, ‘Medium’ and ‘Large’ (Figs. 2.35a-2.35c). Five MFs have been selected for assessing MPCI: ‘Very Small’, ‘Small’, ‘Medium’, ‘Large’ and ‘Very Large’ (Fig. 2.36). Additionally, twenty-seven fuzzy relationships (Figs. 2.37a-2.37b) have been constructed by following IF-THEN rules. By exploring this fuzzy rule base, FIS predicts final output.

Numeric values of MPCIs have been normalized and tabulated in Table 2.33 with corresponding S/N ratios. S/N ratios of MPCIs have been calculated using Higher-is-Better (HB) criterion. Fig. 2.38 represents optimal parametric combination ($N_6 f_1 d_1$). Optimal setting has been obtained by maximizing MPCI by Taguchi's philosophy. As S/N ratio always correspond to Higher-the-Better (HB) criterion; it has been observed that when N is at level 6, f is at level 1 and d is at level 1; mean S/N ratio of MPCI is the maximum. Thus, optimal setting has been predicted as ($N_6 f_1 d_1$). Mean response data for S/N ratio of MPCIs has been shown in Table 2.34.

In the second approach; from the aforementioned three major PCs, the quality loss estimates (with respect to ideal) have been assessed (Table 2.35) as well as normalized. Their representing normalized values have been tabulated in Table 2.36. Individual quality loss estimates (normalized estimates) corresponding to individual PCs (PC1, PC2 and PC3) have been fed as inputs to the Fuzzy Inference System (FIS) with its predicted output termed as NCQL (Fig. 2.39). For assessing NCQL in FIS, the membership functions for the input process variables such as NQL (PC1), NQL (PC2) and NQL (PC3) has been defined as 'Small', 'Medium' and 'Large' (Figs. 2.40a-2.40c). Five MFs have been selected for assessing NCQL: 'Very Small', 'Small', 'Medium', 'Large' and 'Very Large' (Fig. 2.41). Additionally, twenty-seven fuzzy relationships have been constructed by following if-then rules (Fig. 2.42a-2.42b).

Numeric values of NCQL obtained from FIS for all parameter settings have been tabulated in Table 2.36 with corresponding S/N ratios. S/N ratios of NCQL have been computed using Higher-is-Better (LB) criterion. The reason behind criteria selection is that: performance must be maximized and quality loss to be minimized. But while we are talking about normalized quality loss; it must be maximized because normalized value appears maximum 1 for the most ideal situation. Fig. 2.43 represents optimal parametric combination ($N_6 f_1 d_1$). Optimal setting has been obtained by maximizing NCQL by Taguchi's optimization philosophy. As S/N ratio always correspond to Higher-the-Better (HB) criterion; it has been observed that when N is at level 6, f is at level 1 and d is at level 1; mean S/N ratio of NCQL is the maximum. Thus, optimal setting has been predicted as ($N_6 f_1 d_1$). Basically, S/N ratio represents mean (signal) to the noise. Higher S/N ratio signifies lesser noise (i.e. effects of uncontrollable process factors) and thus mean response value approaches to the expected (targeted) level. That's why HB criterion is adapted for optimizing S/N ratio of the response (here NCQL). Mean response table for S/N ratio of NCQLs has also been furnished (Table 2.37).

It has been observed that the predicted optimal setting appeared as $N_6 f_1 d_1$; which is same for both the optimization approaches (i) maximization of MPCI and (ii) maximization of NCQL. The predicted optimal setting represents parameter values: N=2800 [RPM]; f=50 [mm/min] and d=6[mm]. This represents that highest drill speed, lowest feed and lowest drill diameter can produce satisfactory process performance yields in relation of minimum torque, minimum thrust, minimum delamination factor (both at entry as well as exit). Optimal setting has also been validated by confirmatory test.

During FRP composite drilling, with increase in (drill speed) spindle speed temperature at interface area of drilled hole raises which results in softening of matrix material, thereby reducing the chance delamination. Whereas, increase in drill diameter increases the contact area of drilled the hole which tend to increase thrust force and as a consequence an increase in delamination. On the other hand, increase in feed also results in increased delamination due to increase in thrust force.

It has been found that optimal setting has appeared same for both the approaches. This proves application potential of the proposed integrated multi-objective optimization module. At the same time both the approach infer that drill speed is the most significant factor.

2.3.6 Concluding Remarks

Defect free machining, thereby obtaining satisfactory machining performance is indeed a challenging task for CFRP composites. This requires adequate knowledge on the machining process behavior as well as optimization of machining performance features. An appropriate process environment is essentially to be evaluated towards optimizing machining performances. In this context, aforesaid work aimed to optimize thrust force, torque, entry/exit delamination factor in drilling of CFRP composites. An efficient multi-objective optimization methodology has been proposed here by integrating PCA, fuzzy logic in the Taguchi approach. Exploration of the concept of MPCI as well as CQL in the PCA-fuzzy based multi-objective optimization module has been proved fruitful in this context. The said approach can successfully be applied in any other production process (involved with multi-responses) towards continuous quality improvement as well as off-line quality control.

The contribution of this work has been summarized below.

1. Development of PCA-Fuzzy-Taguchi based integrated optimization module of multi-response optimization. A case experimental study has been reported in optimizing multiple output features in machining (drilling) of CFRP epoxy composites.

2. The proposed optimization module introduces the concept of MPCI (Multi-Performance Characteristic Index) as well as NCQL (Normalized Combined Quality Loss) which are new in PCA-Fuzzy-Taguchi based integrated optimization approach.

3. The proposed optimization module is quite efficient in the sense that it can overcome limitation/assumption of existing Taguchi based optimization approaches.

i) It considers response correlation.

ii) Response weight assignment is not required at all.

4. The proposed optimization module explores the concept of maximizing MPCI as well as maximizing NCQL; in both the cases the optimal setting appeared the same. This also proves validity as well as feasibility of MPCI and NCQL concepts in PCA-Fuzzy-Taguchi based optimization approach.

However, this work deals with exhibiting effectiveness of an integrated optimization philosophy through a case experimental research in CFRP composite machining; in-depth study w.r.t. delamination formation, growth and its influence on the property, etc. have not been attempted in detail. This may be investigated in the future work.

Fig. 2.31: CFRP work piece after machining

Fig. 2.32a: Drilled hole diameter at entry (for sample no. 15)

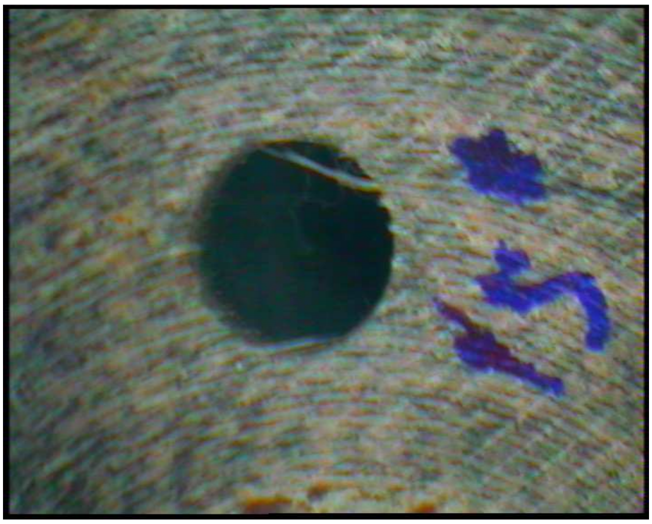


Fig. 2.32b: Drilled hole diameter at exit (for sample no. 15)

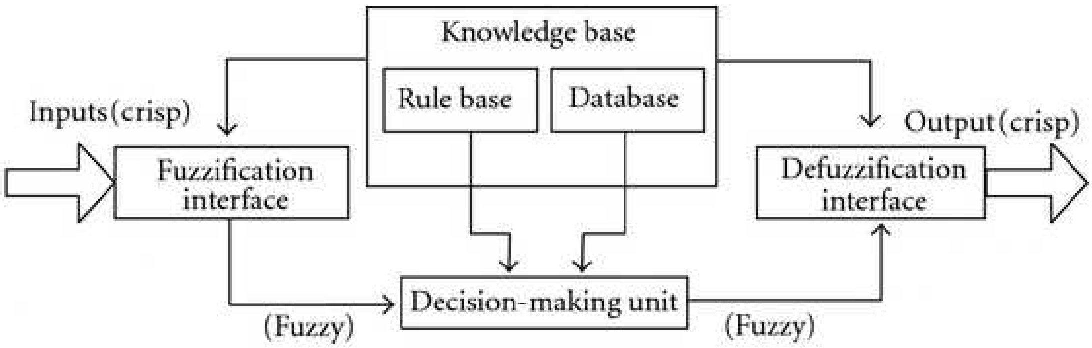


Fig. 2.33: Basic structure of FIS

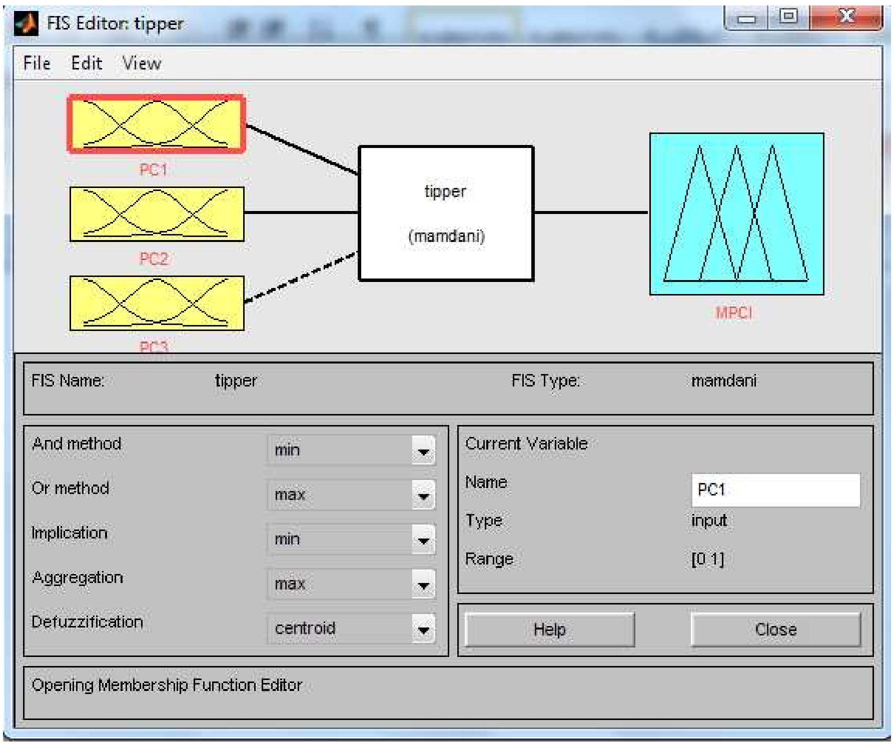


Fig. 2.34: FIS architecture to compute MPCI

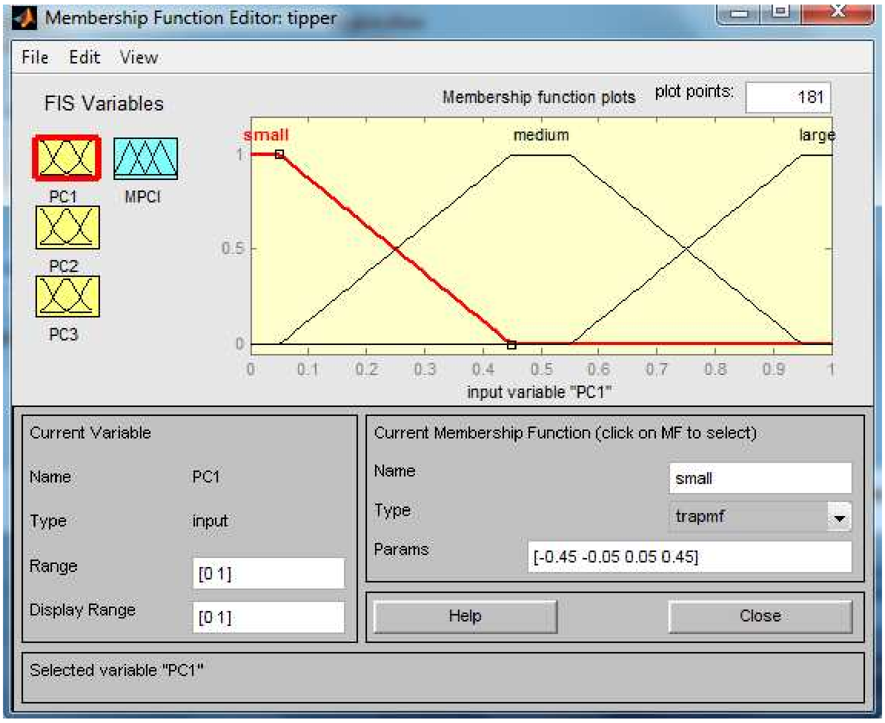


Fig. 2.35a: Membership Functions (MFs) for PC1

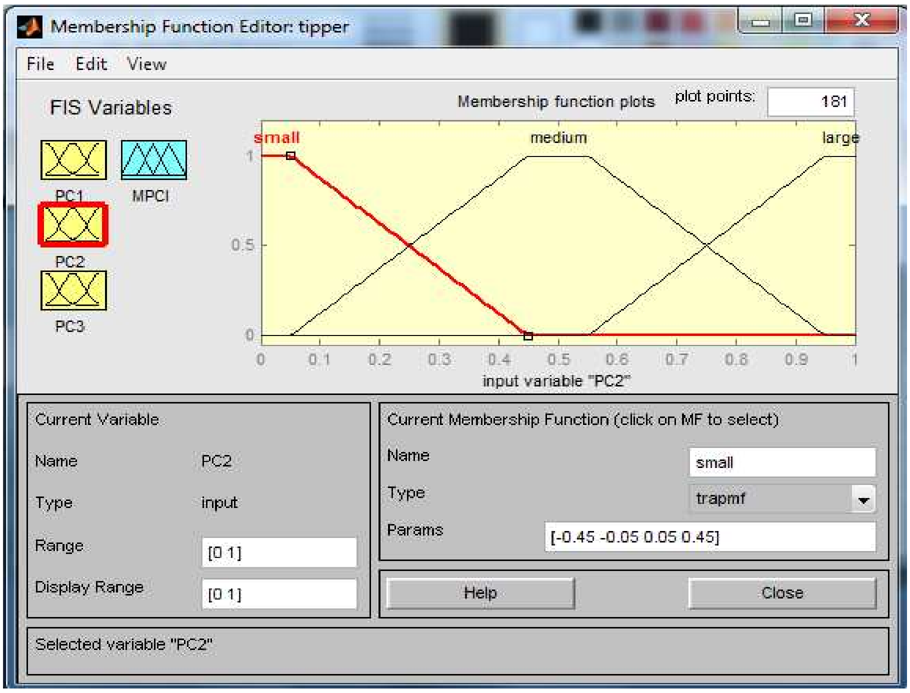


Fig. 2.35b: Membership Functions (MFs) for PC2

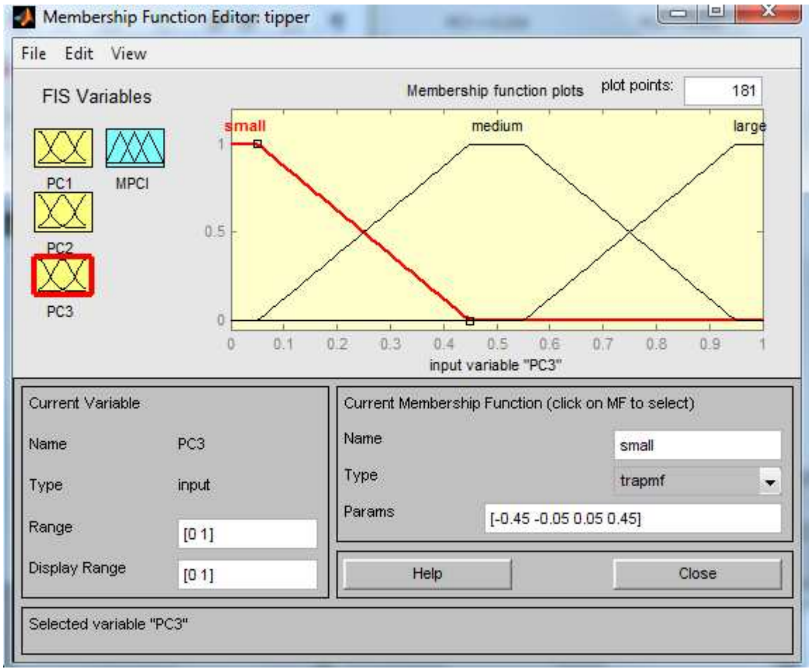


Fig. 2.35c: Membership Functions (MFs) for PC3

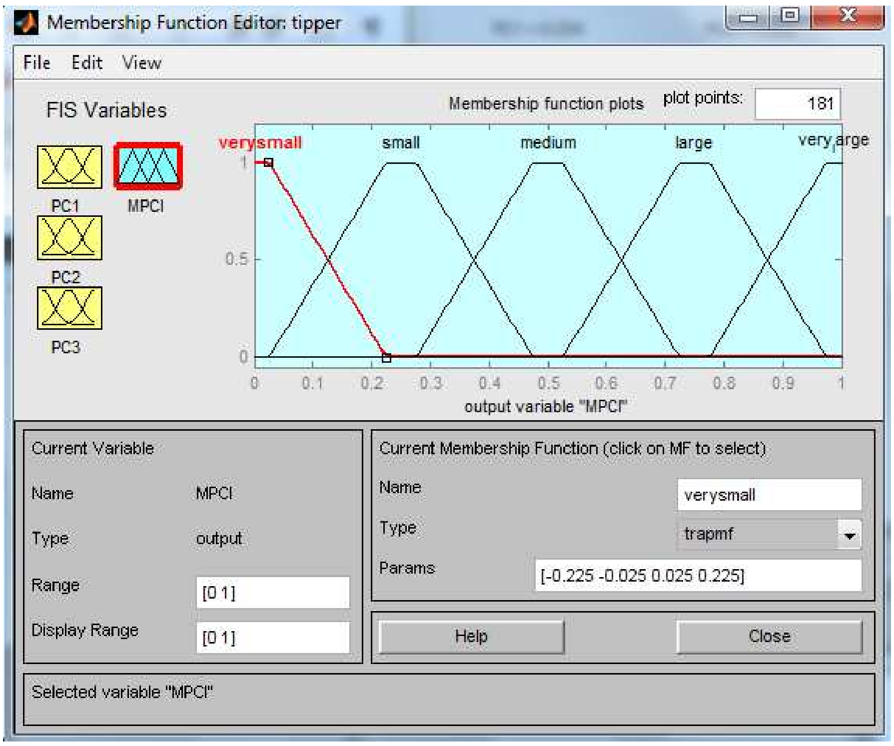


Fig. 2.36: Membership Functions (MFs) for MPCI

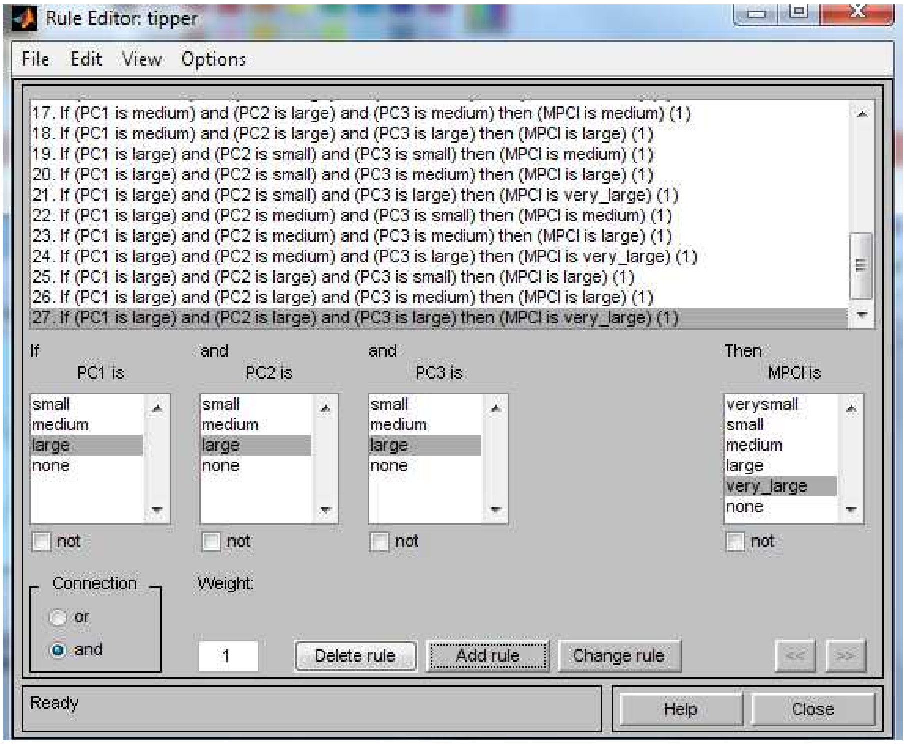


Fig. 2.37a: Fuzzy RULE-BASE

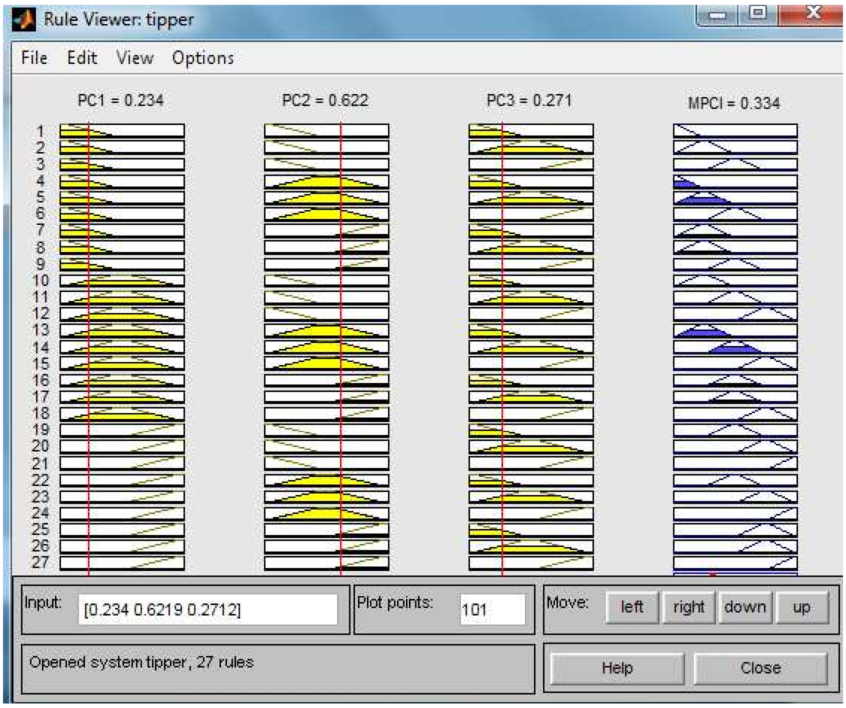


Fig. 2.37b: Computation of MPCI based on fuzzy RULE-BASE

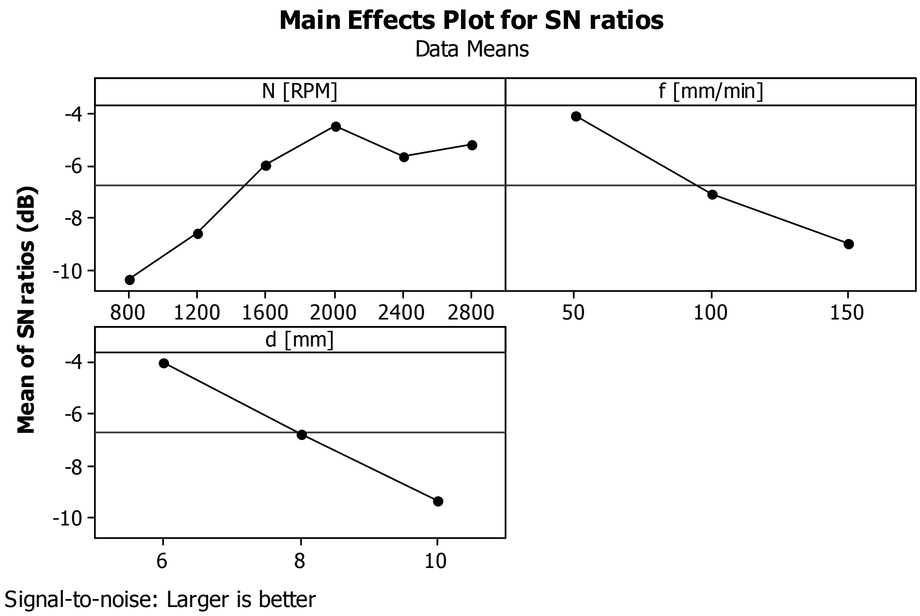


Fig. 2.38: Evaluation of optimal setting (by maximizing MPCI)

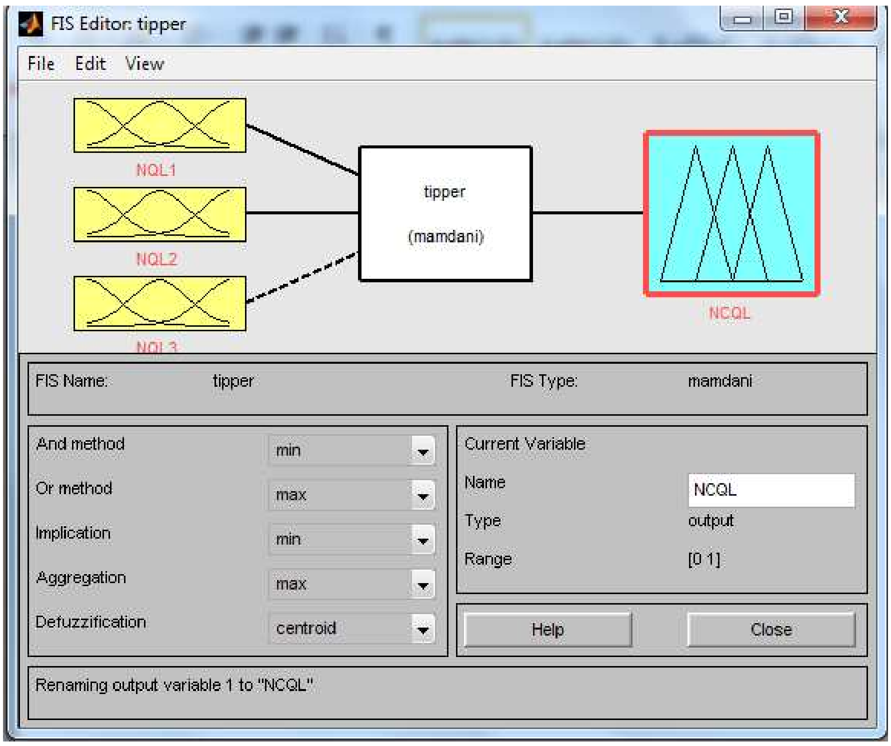


Fig. 2.39: FIS architecture to compute NCQL

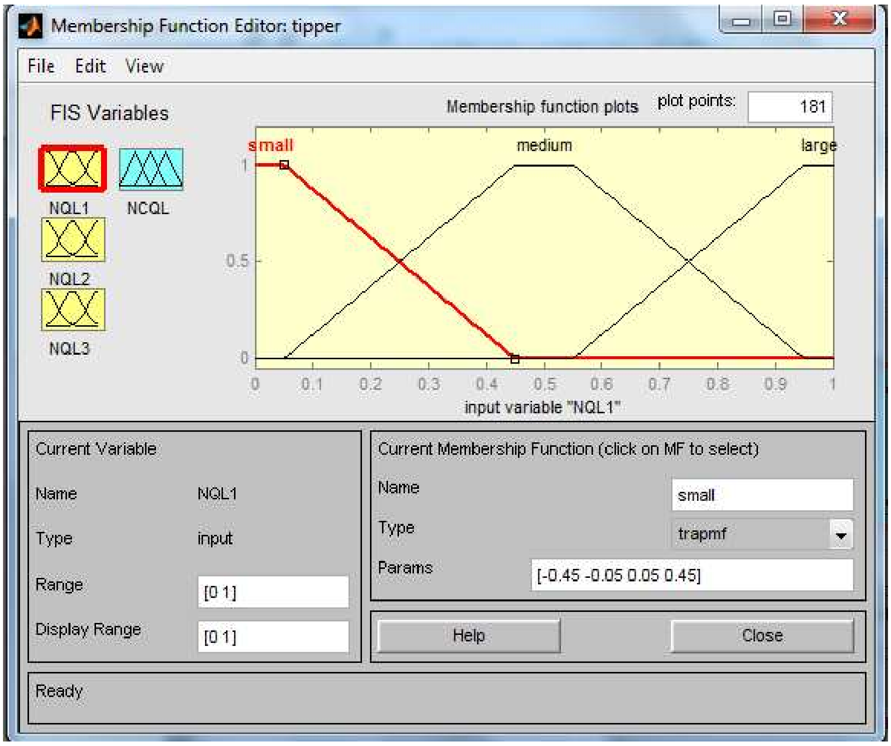


Fig. 2.40a: Membership Functions (MFs) for NQL1 [=NQL(PC1)]

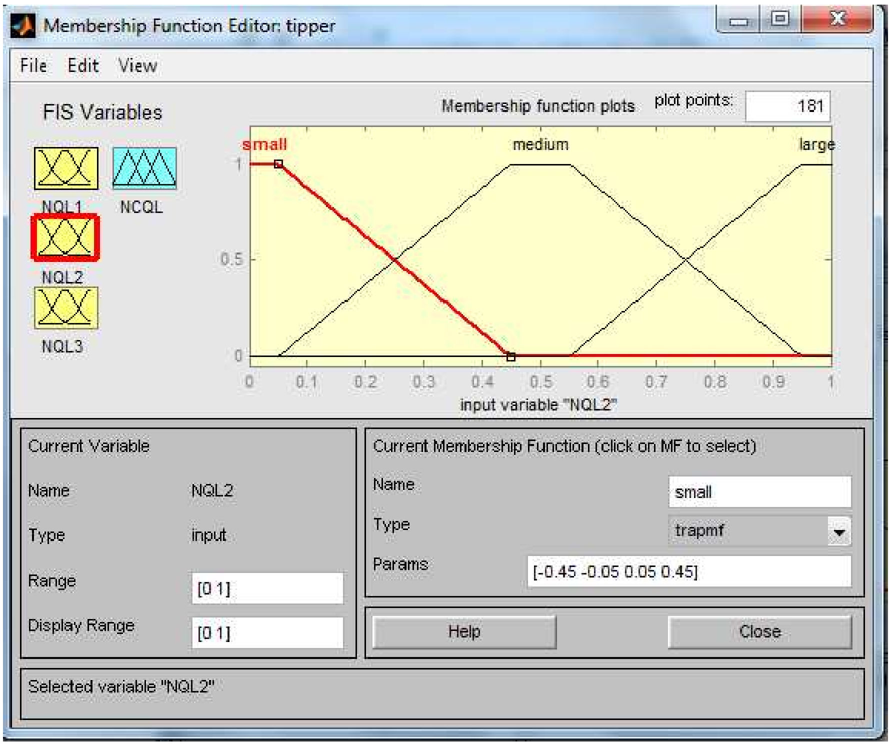


Fig. 2.40b: Membership Functions (MFs) for NQL2 [=NQL(PC2)]

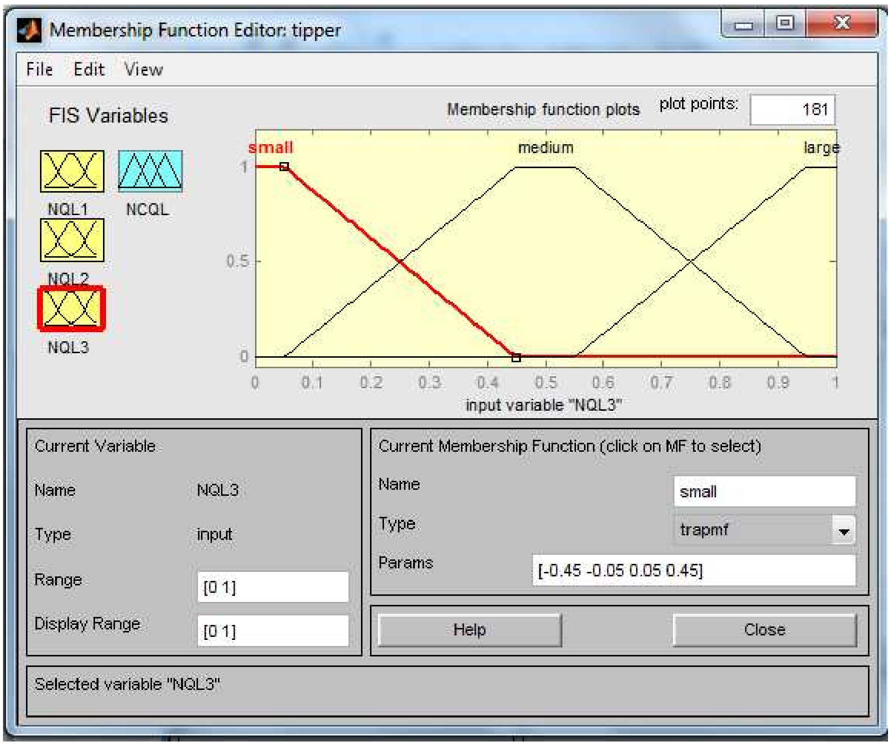


Fig. 2.40c: Membership Functions (MFs) for NQL3 [=NQL(PC3)]

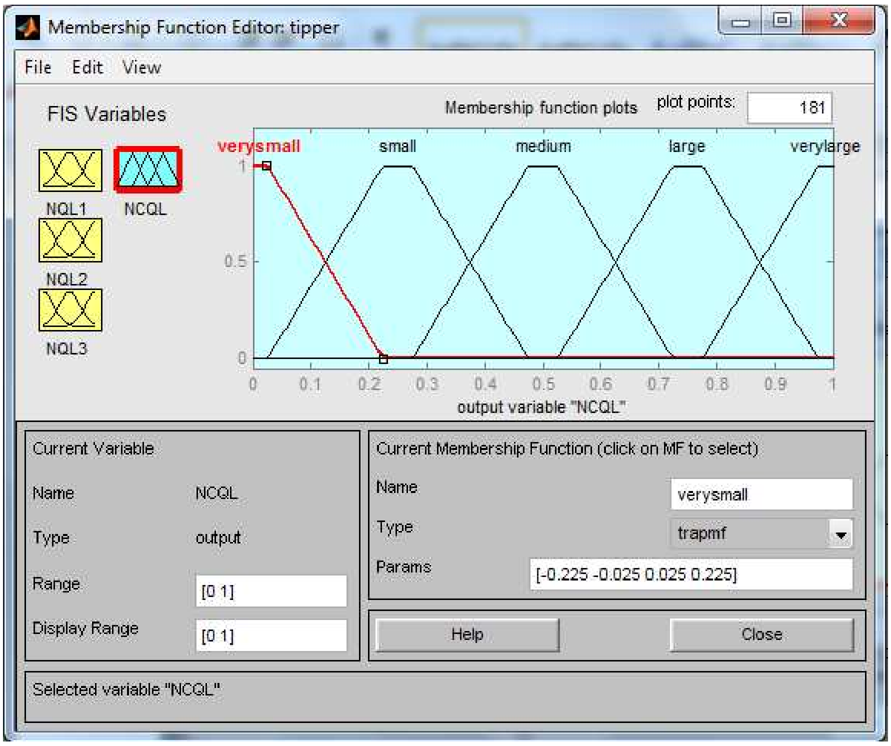


Fig. 2.41: Membership Functions (MFs) for NCQL

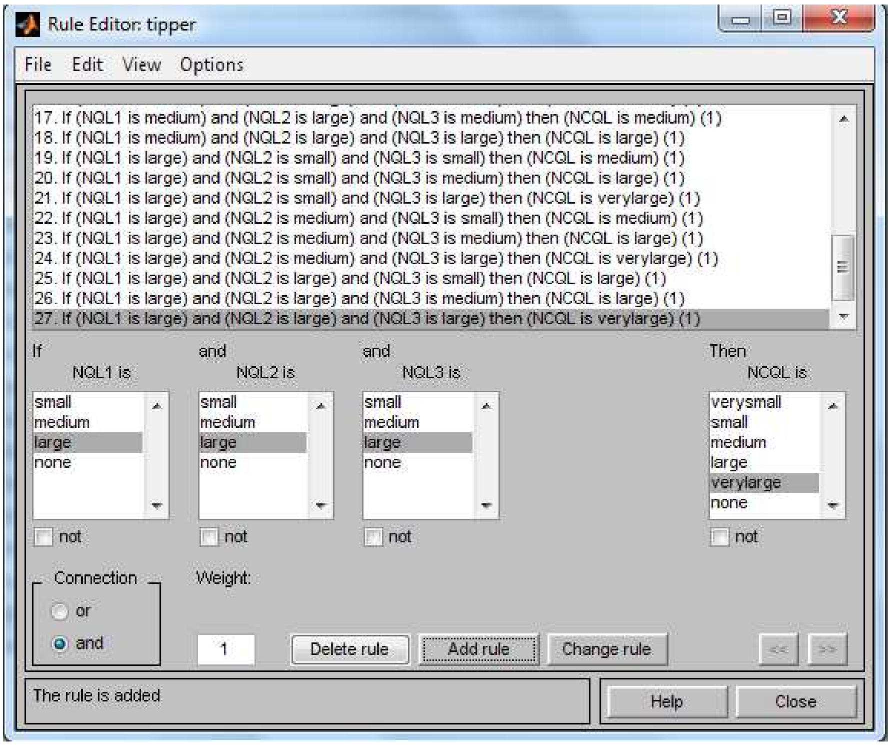


Fig. 2.42a: Fuzzy rule base to compute NCQL

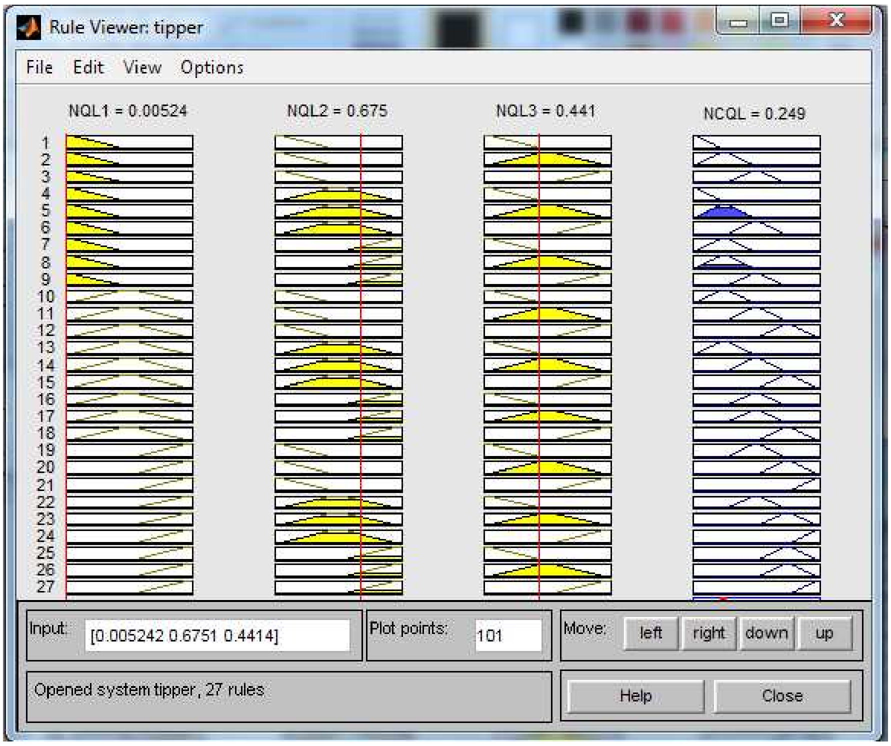


Fig. 2.42b: Computation of NCQL based on fuzzy RULE-BASE

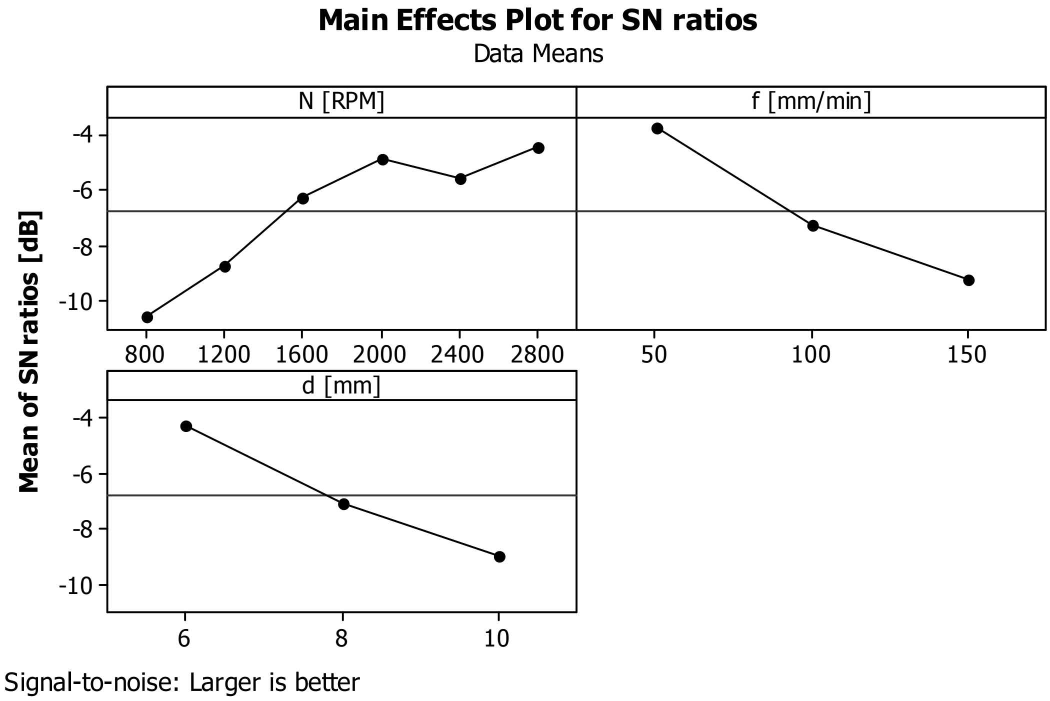


Fig. 2.43: Evaluation of optimal setting (by maximizing NCQL)

Table 2.23: Specification of the work piece material

Sl. No.	Specification/description	Value(s)
01	Density	1.1 g/cm^3
02	Method of Formation	Hand lay Up
03	Temperature	up to 120^0 C
04	Orientation	0/90^0
05	Construction	Epoxy with carbon fibre

Table 2.24: Specification of drills used in the experiments

Sl. No.	Specification/description	Value(s)
01	Product	M1308000RT
02	Shank Type	Plain
03	Overall Length (mm)	79.000
04	Shank Length (mm)	42.000
05	Drill Depth (mm)	27.000
06	Flute Length (mm)	37.000
07	Shank Size (mm)	8.000
08	Material	Solid Carbide
09	Point	118^0
10	Type	High Performance Drill
11	Number of Flutes	2
12	Drill Style	Metric
13	Coating	TiAlN

Table 2.25: Design of Experiment (A mixed-level L_{18} Orthogonal Array)

Sl. No.	Drill Speed [RPM]	Feed [mm/min]	Drill Diameter [mm]
01	800	50	6
02	800	100	8
03	800	150	10
04	1200	50	6
05	1200	100	8
06	1200	150	10
07	1600	50	8
08	1600	100	10
09	1600	150	6
10	2000	50	10
11	2000	100	6
12	2000	150	8
13	2400	50	8
14	2400	100	10
15	2400	150	6
16	2800	50	10
17	2800	100	6
18	2800	150	8

Table 2.26: Domain of Experiments

Factors	Unit	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Drill Speed	[RPM]	800	1200	1600	2000	2400	2800
Feed	[mm/min]	50	100	150	-	-	-
Drill diameter	[mm]	6	8	10	-	-	-

Table 2.27: Experimental data

Sl. No.	Thrust [kN]	Torque [kN-mm]	Entry Delamination Factor	Exit Delimitation Factor
01	0.402069	0.010787	1.033859	1.005681
02	0.647232	0.010787	1.072158	1.020928
03	0.5982	0.074531	1.060688	1.057778
04	0.25497	0.012749	1.068361	1.062752
05	0.500134	0.008826	1.000345	1.006784
06	0.549167	0.062763	1.045369	1.041532
07	0.31381	0.005884	1.038655	1.057804
08	0.470714	0.033343	1.053015	1.045369
09	0.372649	0.008826	1.027328	1.031251
10	0.197112	0.013729	1.049205	1.045369
11	0.333423	0.010787	1.028996	1.005503
12	0.500134	0.005884	1.057804	1.043451
13	0.25497	0.006865	1.067395	1.080261
14	0.402069	0.043149	1.056852	1.0532
15	0.294197	0.01471	1.005196	1.03677
16	0.205938	0.017652	1.053015	1.030049
17	0.225551	0.003923	1.006078	1.026971
18	0.460908	0.030401	1.0626	1.043451

Table 2.28: Computed S/N ratio of the responses

Sl. No.	S/N Ratio (Thrust)	S/N Ratio (Torque)	S/N Ratio (Entry Delamination Factor)	S/N Ratio (Exit Delamination Factor)
1	7.9140	39.3420	-0.289226	-0.049205
2	3.7788	39.3420	-0.605176	-0.179902
3	4.4631	22.5533	-0.511753	-0.487891
4	11.8702	37.8905	-0.574361	-0.528639
5	6.0183	41.0847	-0.002996	-0.058726
6	5.2059	24.0459	-0.385392	-0.353452
7	10.0667	44.6065	-0.329426	-0.488104
8	6.5449	29.5399	-0.448691	-0.385392
9	8.5740	41.0847	-0.234183	-0.267288
10	14.1057	37.2472	-0.417207	-0.385392

11	9.5401	39.3420	-0.248274	-0.047667
12	6.0183	44.6065	-0.488104	-0.369441
13	11.8702	43.2672	-0.566503	-0.670574
14	7.9140	27.3006	-0.480283	-0.450217
15	10.6272	36.6477	-0.045015	-0.313648
16	13.7253	35.0641	-0.448691	-0.257158
17	12.9351	48.1276	-0.052633	-0.231164
18	6.7277	30.3422	-0.527396	-0.369441

(S/N Ratio ~ Signal-to-Noise Ratio (dB))

Table 2.29: Computed normalized S/N ratios

Sl. No.	Normalized S/N Ratios			
	Thrust	Torque	Entry Delamination Factor	Exit Delamination Factor
Ideal Situation	1	1	1	1
1	0.400427	0.656454	0.524683	0.997536
2	0.000	0.656454	0.000	0.787715
3	0.066261	0.000	0.155148	0.293272
4	0.783525	0.599697	0.05118	0.227856
5	0.216857	0.724597	1.00000	0.982251
6	0.138193	0.058352	0.364987	0.509099
7	0.60888	0.862307	0.457926	0.29293
8	0.267849	0.273176	0.259871	0.457823
9	0.464339	0.724597	0.616091	0.647427
10	1	0.574545	0.312154	0.457823
11	0.557889	0.656454	0.59269	1.00000
12	0.216857	0.862307	0.19442	0.48343
13	0.783525	0.809935	0.064228	0.00
14	0.400427	0.185615	0.207407	0.353753
15	0.663162	0.551104	0.930228	0.573
16	0.963158	0.489182	0.259871	0.66369
17	0.886643	1.000	0.917578	0.70542
18	0.285556	0.304549	0.12917	0.48343

Table 2.30: Check for correlation

Correlation between	Pearson's Correlation Coefficient	P-Value (probability of significance)
Thrust & torque	0.500	0.029
Thrust & entry delamination	0.302	0.209
Thrust & entry delamination	0.454	0.051
Thrust & exit delamination	-0.028	0.908
Torque & exit delamination	0.313	0.192
Entry delamination & exit delamination	0.635	0.003

Table 2.31: Results of PCA

	PC1	PC2	PC3	PC4
Eigen value	1.8515	1.3065	0.5214	0.3206
Eigen vector	$\begin{vmatrix} 0.965 \\ 0.225 \\ 0.100 \\ -0.127 \end{vmatrix}$	$\begin{vmatrix} 0.115 \\ -0.104 \\ -0.307 \\ -0.940 \end{vmatrix}$	$\begin{vmatrix} 0.219 \\ 0.956 \\ 0.169 \\ 0.104 \end{vmatrix}$	$\begin{vmatrix} 0.086 \\ 0.159 \\ 0.931 \\ 0.299 \end{vmatrix}$
AP	0.463	0.327	0.130	0.080
CAP	0.463	0.790	0.920	1.000

Table 2.32: Computed major Principal Components (PCs)

Sl. No.	PC1	PC2	PC3
Ideal Situation	1.163	-1.236	1.448
1	0.459896	-1.12098	0.907678
2	0.047663	-0.80873	0.709493
3	0.042208	-0.31569	0.071219
4	0.867214	-0.20216	0.777249
5	0.347557	-1.28074	1.011362
6	0.118329	-0.58078	0.200678
7	0.790178	-0.4356	1.065564
8	0.287782	-0.50774	0.411347
9	0.590507	-0.81968	0.965857
10	1.067344	-0.47094	0.868632
11	0.618334	-1.12607	0.953912
12	0.361333	-0.57885	0.954991
13	0.944761	-0.01384	0.956744
14	0.40399	-0.36946	0.336984
15	0.784202	-0.80525	0.888889
16	0.981211	-0.64376	0.791531
17	1.082777	-0.94683	1.378597
18	0.295606	-0.49291	0.425792

Table 2.33: Normalized PCs and aggregated MPCI as obtained from FIS

Sl. No.	Normalized PCs			MPCI	Corresponding S/N Ratio [dB]
	PC1	PC2	PC3		
1	0.385756	0.1261	0.639799	0.515	-5.7639
2	0.005038	0.372574	0.488209	0.25	-12.0412
3	0	0.761745	0	0.215	-13.3512
4	0.761935	0.851354	0.540035	0.631	-3.9994
5	0.282005	0	0.719106	0.5	-6.0206
6	0.070301	0.552498	0.099022	0.162	-15.8097
7	0.690789	0.667096	0.760564	0.655	-3.6752
8	0.2268	0.61015	0.26016	0.329	-9.6561
9	0.506383	0.363927	0.684299	0.59	-4.5830
10	0.946766	0.6392	0.609933	0.754	-2.4526
11	0.532082	0.122082	0.675163	0.585	-4.6569
12	0.294728	0.554019	0.675988	0.486	-6.2673
13	0.833554	1	0.677329	0.688	-3.2482
14	0.334124	0.719301	0.203281	0.341	-9.3449
15	0.685269	0.375317	0.625427	0.602	-4.4081
16	0.867218	0.502786	0.55096	0.551	-5.1770
17	1	0.263568	1	0.914	-0.7811
18	0.234026	0.621853	0.271209	0.334	-9.5251

Table 2.34: Mean response table for S/N ratio of MPCIs

Level	Drill speed	Feed	Diameter of drill
1	-10.385	-4.053	-4.032
2	-8.610	-7.083	-6.796
3	-5.971	-8.991	-9.299
4	-4.459	-	-
5	-5.667	-	-
6	-5.161	-	-
Delta	5.927	4.938	5.267
Rank	1	3	2

Table 2.35: Computed QL corresponding to individual PCs

QL (PC1)	QL (PC2)	QL(PC3)
0.703104	0.115016	0.540322
1.115337	0.427275	0.738507
1.120792	0.920315	1.376781
0.295786	1.03384	0.670751
0.815443	0.044737	0.436638
1.044671	0.65522	1.247322
0.372822	0.800404	0.382436

0.875218	0.728259	1.036653
0.572493	0.41632	0.482143
0.095656	0.765063	0.579368
0.544666	0.109926	0.494088
0.801667	0.657147	0.493009
0.218239	1.22216	0.491256
0.75901	0.866543	1.111016
0.378798	0.430749	0.559111
0.181789	0.59224	0.656469
0.080223	0.289174	0.069403
0.867394	0.743086	1.022208

NB: QL(PC) ~ Quality loss estimate for individual PCs

Table 2.36: Computed NQL corresponding to individual PCs and NCQL

Normalized Quality Loss Estimates for individual PCs			Normalized Combined Quality Loss Estimates (NCQL)	Corresponding S/N Ratio [dB]
NQL(PC1)	NQL(PC2)	NQL(PC3)		
0.401403	0.940311	0.578391	0.483	-6.3211
0.005242	0.675106	0.441351	0.249	-12.0760
0.0000	0.256361	0.0000	0.215	-13.3512
0.792841	0.159942	0.488202	0.646	-3.7953
0.293444	1	0.650085	0.471	-6.5396
0.073153	0.481509	0.089518	0.159	-15.9721
0.718809	0.358202	0.687565	0.632	-3.9857
0.236	0.419476	0.23519	0.328	-9.6825
0.526923	0.68441	0.61862	0.550	-5.1927
0.985169	0.388218	0.551391	0.750	-2.4988
0.553664	0.944634	0.61036	0.545	-5.2721
0.306683	0.479872	0.611106	0.453	-6.8780
0.867365	0.000	0.612318	0.696	-3.1478
0.347677	0.30203	0.18377	0.343	-9.2941
0.713065	0.672155	0.565398	0.606	-4.3505
0.902394	0.534999	0.498078	0.712	-2.9504
1	0.792397	0.904019	0.914	-0.7811
0.243519	0.406884	0.245178	0.332	-9.5772

NB: NQL(PC) ~ Normalized Quality loss estimate for individual PCs

Table 2.37: Mean response table for S/N ratio of NCQLs

Level	Drill speed	Feed	Diameter of drill
1	-10.583	-3.783	-4.285
2	-8.769	-7.274	-7.034
3	-6.287	-9.220	-8.958
4	-4.883	-	-
5	-5.597	-	-
6	-4.436	-	-
Delta	6.147	5.437	4.673
Rank	1	2	3

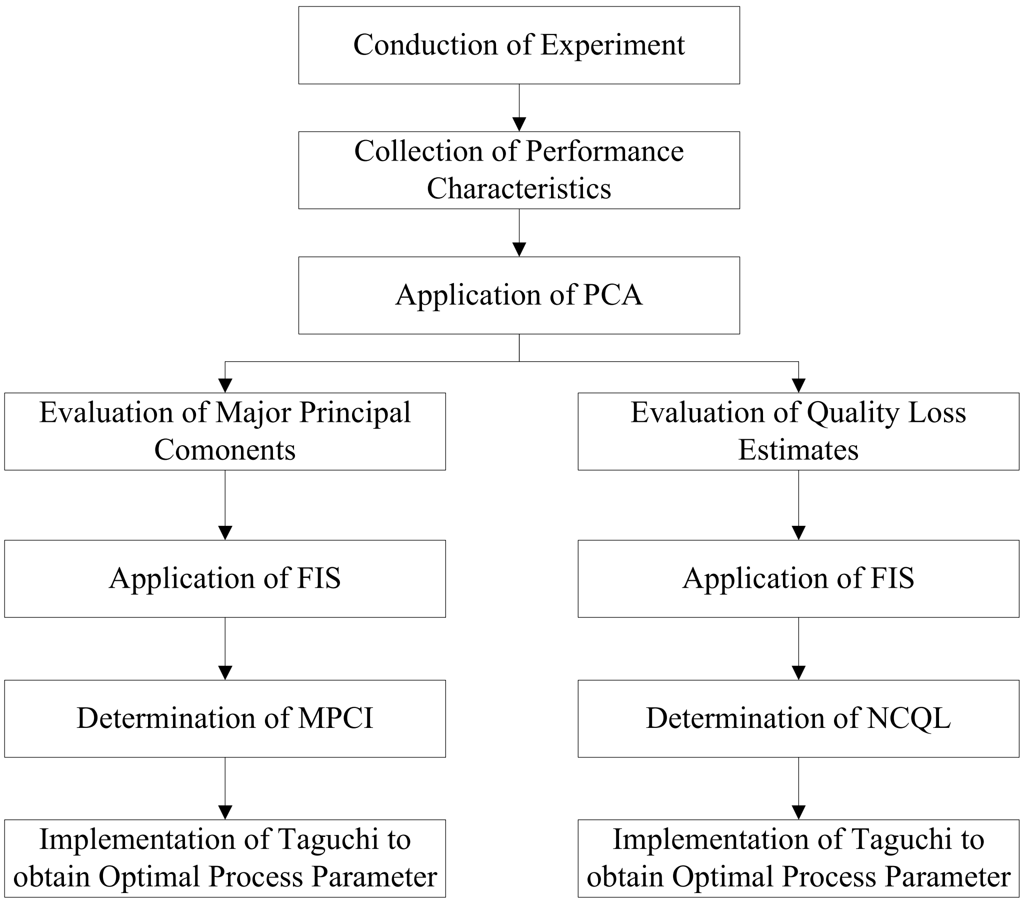


Fig. 2.44: Block diagram of the proposed optimization module

CHAPTER 3

EXPERIMENTAL INVESTIGATIONS ON TURNING: PARAMETRIC OPTIMIZATION

3.1 Parametric Appraisal and Optimization in Machining of CFRP (Epoxy) Composites by Using TLBO (Teaching-Learning Based Optimization) Algorithm

3.1.1 Coverage

The present work focuses on machining (turning) aspects of CFRP (epoxy) composites by using single point HSS cutting tool. The optimal setting i.e. the most favorable combination of process parameters (such as spindle speed, feed rate, depth of cut and fiber orientation angle) has been derived in view of multiple and conflicting requirements of machining performance yields viz. Material Removal Rate (MRR), surface roughness, SR (R_a) (of the turned product) and cutting force. This study initially derives mathematical models (objective functions) by using statistics of nonlinear regression for correlating various process parameters with respect to the output responses. In the next phase, the study utilizes a recently developed advanced optimization algorithm TLBO (Teaching-Learning Based Optimization) in order to determine the optimal machining condition for achieving satisfactory machining performances. Application potential of TLBO algorithm has been compared to that of Genetic Algorithm (GA). It has been observed that exploration of TLBO appears more fruitful in contrast to GA in the context of this case experimental research focused on machining of CFRP composites.

Definition for the abbreviations

X_1= spindle speed,
X_2= feed rate,
X_3= depth of cut,
X_4= orientation of fiber
F_x= feed force
F_y= tangential force
F_z= longitudinal force
Z_1= mathematical equation for cutting force
Z_2= mathematical equation for surface roughness
Z_3= mathematical equation for Material removal rate (MRR)
Z= mathematical equation for multi objective
CF= cutting Force
SR= surface roughness
MRR= Material Removal Rate
TLBO= Teaching-Learning Based Optimization
ABC= Artificial Bee Colony
ACO= Ant Colony Optimization
PSO= Particle Swarm Optimization
SA= Simulated Annealing
GA= Genetic algorithm

3.1.2 Problem Definition

Literature is reach enough in investigating machining and machinability aspects of FRP (fibre reinforced polymer) composites especially on GFRP. Compared to GFRP, lesser extent of research was carried out on machining of CFRP composites. To this end, the present study attempts to focus on CFRP machining through generating a mathematical model for the process parameters (in relation to machining responses); and thereby, investigating the influences of the process parameters on different output performance characteristics. A newly developed Teaching-Learning Based Optimization (TLBO) approach has been utilized here for assessing optimal machining environment for improvement of quality and productivity while performing turning operation of CFRP composites. Because, it is felt that, during machining, there should be compatible balance between quality and productivity which include high production rate with reduced cost as well as to maintain good surface finish as well as dimensional accuracy. Hence, the concept of optimization in manufacturing (production context) came into existence which aims to minimize/maximize objective function for evaluation of most favourable machining conditions from the number of possible alternatives (process environments).

In practice, any product/process is evaluated by means of overall quality/performance which in turn is characterized by multiple quality or performance features. During machining operation, evaluation of the most appropriate process environment (parameters setting) is of utmost important in view of desired product quality as well as process performance. This can be achieved by optimization of machining yields. Optimization of single objective may not be fruitful always as simultaneous fulfilment of multi-objectives (to the maximum possible extent) is indeed necessary. Traditional Taguchi method is widely applied in solving a variety of optimization problems in the field of manufacturing. However, shortcoming of this method is that it cannot solve multi-objective optimization problems. Moreover, Taguchi method searches optimal at some discrete levels of process parameters in a given search domain. Therefore, desirability function, grey relation analysis, utility theory as well as TOPSIS could be integrated with Taguchi method to solve multi-objective optimization problems. Due to discrete search philosophy of Taguchi based optimization approaches, the optimal setting thus obtained may not always research the global optima. In order to get rid of those, mathematical models need to be developed which represent functional relationship amongst inputs (process variables) as well as output responses. These models are to be optimized by the help of an optimization algorithm. Different evolutionary optimization algorithms (GA, PSO, SA) were developed by pioneers and well documented in literature (Vahdani et al. 2012; Chaube et al., 2012; Kumar et al., 2010; Bachlaus et al., 2008; Lin et al., 2012; Akay and Karaboga, 2012).

In real world scenario, several conflicting responses (i.e. output characteristics) affect the optimized aggregated objective value because of their nonlinear characteristics. The objective function may be multimodal (i.e. more than one local minimum or maximum); but emphasis is being paid to evaluate the global optimal values within the given search domain. Traditional methods of optimization techniques are found inefficient to handle these types of problems. Hence, advanced heuristic and meta-heuristic optimization algorithms are being implemented which can efficiently handle different types of optimization problems; when the objective functions may be stationary or non-stationary (time-dependent); linear or nonlinear, continuous or discontinuous. The unified aim is to find solution near to the global optimum in less time and with less computational effort.

For optimization problems, heuristic algorithms use to obtain a solution using 'trial-and-error' computation in a reasonable time frame. The solution obtained may not be the best solution of all the actual solutions but it may be a good approximation to the exact solution. But these methods are quite popular in demand because they do not require a too long time to obtain a solution (Yang 2009).

Meta-heuristics are considered as modern higher-level algorithms (techniques or strategies) including Genetic Algorithm (GA), Simulated Annealing (SA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Bee Algorithms (BA), Firefly Algorithms (FA), Teaching-Learning-Based Optimization (TLBO), Imperialist Competitive Algorithm (ICA) and Harmony Search (HS) that intend to combine lower-level techniques and tactics for exploration and exploitation of the huge solution space. These optimization techniques include two major components intensification (exploitation) and diversification (exploration) to obtain optimal or nearly optimal solution. Some authors also presented modified GA and SA as Meta-heuristics.

Majority of these techniques are mainly based on nature based optimization ideology. The most common evolutionary method is genetic algorithm which is based on principles of genetics and evolution, and mimics the reproduction behaviour observed in biological populations. Particle Swarm Optimization (PSO) technique is a meta-heuristic technique which is basically inspired by social behaviour of animals such as fish schooling or birds flocking; whereas, Ant Colony Optimisation (ACO) is motivated by foraging behaviour of real life ant colonies. Simulated Annealing (SA) is the process in which a substance is virtually heated above its melting point and then slowly cooled down to minimize the energy distribution. These modern meta-heuristics techniques are utilized to solve different optimization problems in various fields such as industrial planning, scheduling, decision making and pattern recognition, process parameter selection in machining and many others.

Now-a-days, application of meta-heuristic techniques has remarkably increased in the field of production and industrial engineering specially in optimizing machining process parameters (Table 3.1).

The drawback of majority of these algorithms is that they require a set of tuning parameters which need to be adjusted so that the algorithms can perform efficiently. However, it is felt difficult to obtain optimized values of those tuning parameters for ensuring maximum performance of the said algorithm. In contrast to existing algorithms (GA, PSO, SA); Teaching-Learning-based optimization (TLBO) is one of the recently proposed population based algorithms which simulates the teaching-learning process of the class room. This algorithm does not require any algorithm-specific control parameters. A numbers of papers could be found in literature source towards in-depth understanding of TLBO (Rao et al., 2011a; Satapathy and Naik, 2011; Rao et al., 2012a; Crepinšek et al., 2012; Rao et al., 2012b; González-Álvarez et al., 2012; Rao and Patel 2013; Rao and Kalyankar, 2013; Satapathy et al., 2013a; Rao and Waghmare, 2013; Satapathy et al., 2013b; Rao and Waghmare, 2014a; Krishnasamy and Nanjundappan, 2014; Rao and Waghmare, 2014b).

Motivated by this, present work explores TLBO algorithm in optimizing multiple process performance yields during turning of CFRP composites. The uniqueness of this work on machining (turning) of CFRP is the selection of appropriate machining parameters (combination of spindle speed, feed and depth of cut) towards optimizing (MRR, surface roughness and cutting force) during machining of CFRP (epoxy) composites through nonlinear regression and TLBO analysis. Application of TLBO in optimizing machining performances during CFRP composites has not been reported before.

3.1.3 Experimental Work

Tuning operations have been carried out on lathe (Make: PINACHO, Spain). Spindle speed, feed rate, depth of cut and fibre orientation has been considered as the process parameters. The domain of process parameters for this experimentation has been shown Table 3.2.

Statistical software package MINITAB 16 has been employed to achieve the Box-Behnken design of experiment (Table 3.3) and also to establish a mathematical model (input-output relationship) based on non-linear regression.

This work utilizes the Box-Behnken design module in RSM for designing the experimental runs. The process parameters viz. spindle speed, feed rate, depth of cut and orientation of fibre has been varied into three discrete levels. The actual parameter has been converted into coded form by using the following relation.

$$Coded\ Value\ (C) = \frac{X - \frac{X_{\max} + X_{\min}}{2}}{\frac{X_{\max} - X_{\min}}{2}}$$

Here, C is coded value (-1, 0, 1) and X_{max} and X_{min} are the actual maximum and minimum parametric setting and X is the actual value of corresponding variable.

As, 67.5^0 orientation of fibre for CFRP composite is not available for this experimentation, this work utilizes the 60^0 orientation CFRP composite material bar in this experimentation. The nonlinear regression model presented here is in the natural form (uncoded form).

Turning operation has been carried on samples of CFRP epoxy composite bars (ø50x150 mm) (Density: $1.1 gm/cm^3$, Composition: 30% fibre and 70% epoxy) with single point HSS turning tool. Method of formation of the specimens was hand layup. The method involved applying or laying the reinforcement material into the mould manually. In this process, epoxy resin was applied by hand and reinforcing material (carbon fibre mat) which were carefully applied and brushed into the open mould. A total number of 27 experiments have been conducted as per 27 setting of process parameters depicted in Table 3.3. Material Removal Rate (MRR), roughness average (R_a) and cutting force etc. have been considered as machining performance characteristics.

Material Removal Rate (MRR) can be defined as the volume of material removed while machining divided by the machining time. MRR for each experimental run has been evaluated by using following equation:

$$MRR = \frac{(W_i - W_f)}{\rho . t_m} \frac{mm^3}{\min} \tag{3.1}$$

W_i = Initial weight of the work piece, W_f = Final weight of the work piece, ρ = Density of the work material, t_m = Machining time.

Surface roughness can be understood as the level (extent) of unevenness of the machined part's surface and is considered as the most important variable in explaining surface finish. Surface roughness tester SJ-210 (Make: Mitutoyo) has been utilized for determining the roughness average (R_a) values. For a particular work piece, three values for R_a have been computed and average of these values has been taken for further analysis.

From literature, it is known that surface roughness increases with the increase of fiber orientation angle due to the compressive strain generated in the work material. Increase in depth of cut leads to good surface finish because when depth of cut is low, the fibers are removed from matrix partially which results in high surface roughness; whereas, when depth of cut is high there is possibility of complete removal of fibers which leads to good surface finish. At low speed and high feed, there is less chance of debonding and fiber breakage which improves the surface finish. The effects of turning process parameters on various output responses during machining of CFRP composites could be found in (Rajasekaran et al., 2012; Li et al., 2014).

Cutting forces are mainly responsible for the fibre pull out in machining of fibre reinforced (FRP) composites; and hence, it is required to minimize the cutting forces developed during operation. Cutting tool dynamometer (Computerized Lathe Tool Dynamometer, Make: MEDILAB ENTERPRISES, Chandigarh, INDIA) has been used whilst performing turning for assessment of cutting forces in all three directions (F_X, F_Y and F_Z). The resultant cutting force (F_r) has been computed as below (Fig. 3.12):

$$F_r = \sqrt{F_x^2 + F_y^2 + F_z^2} \tag{3.2}$$

Experimental data as furnished in Table 3.3 have been analyzed further. It has been assumed that: (i) there is no interactive effect of process parameters on output (response) characteristics, and, (ii) Output characteristics i.e. machining performance features are uncorrelated to each other.

3.1.4 Nonlinear Regression

A nonlinear regression is a type of regression analysis in which observed data are modelled by a function which is a nonlinear combination of the model parameters and depends on one or more independent variable(s). The data are fitted by successive approximations method. Nonlinear regression plays a significant role to recognize the complex interrelationship amongst the variables. As compared to linear regression, there may be many local minima of the function to be optimized and even the global minimum may produce a biased estimate. In practice, estimated values of the parameters are used, together with the optimization algorithm for evaluating the global minimum of a sum of squares.

Proper execution of experiments is indeed essential for developing an adequate mathematical model based upon the experimental data. In this study, mathematical models have been developed using non-linear regression based on experimental results. The aim of developing mathematical model here is that to relate performance characteristics to their process parameters; in order to facilitate the machining process. The proposed model for each response (process output characteristic) has presented as below:

$$Y_u = C * X_1^a * X_2^b * X_3^c * X_4^d \tag{3.3}$$

Here C represents the constant; X_1 represents spindle speed; X_2 represents feed rate; X_3 is the depth of cut; X_4 is fibre orientation. a, b, c, d are estimated coefficients of the said regression model.

[Source: Thirumalai and Senthilkumaar, 2013; www.Wikipedia .com]

In the present work, Gauss-Newton algorithm has been used to generate the coefficients, with maximum iterations at 200, and a tolerance value of 0.00001.

3.1.5 TLBO (Teaching-Learning Based Optimization)

In traditional Taguchi based optimization approaches such as desirability function approach, grey relation theory, principal component analysis etc.; response weights are to be assigned which mainly depend on the discretion of the decision-makers. This may cause uncertainty as well as inaccuracy in deriving the optimal solution. It led to emerging new evolutionary algorithms which are capable to solve different optimization problems effectively and efficiently. These algorithms are nature-based algorithm and it is assumed that the behavior of nature is always the best in its performance. Amongst several evolutionary techniques, TLBO is gaining more attention now-a-days which is basically a population-based method and uses a population of solutions to obtain the global solution. Rao et al. (2011) initially proposed the Teaching-Learning Based Optimization (TLBO) algorithm generally considered as population based model which takes account of mimics of teaching-learning interaction of a teacher and students (learners) in a class room. Rao and Kalyankar (2011) also highlighted advantages of TLBO; compared the results with previous optimization technique such as artificial bee colony and concluded that TLBO provides better result in terms of population size, number of generations and computational time. The TLBO algorithm includes teacher and learners which are vital components of this model, describes the two modes of learning, firstly by teacher who is highly qualified (teacher phase) and other one by the interacting with students (considered as a learner phase).

In another reporting, (Rao and Patel, 2012; 2013) introduced elitism concept in the TLBO algorithm; and its effect on the performance of the algorithm was investigated. The effects of common controlling parameters such as the population size and the number of generations on the performance of the algorithm were also investigated.

The concept of elitism is utilized in most of the evolutionary and swarm intelligence algorithms where during every generation the worst solutions are replaced by the elite solutions. In the TLBO algorithm, after replacing the worst solutions with elite solutions at the end of learner phase, if the duplicate solutions exist then it is necessary to modify the duplicate solutions in order to avoid trapping in the local optima. In the work (Rao and Patel, 2012; 2013), duplicate solutions were modified by mutation on randomly selected dimensions of the duplicate solutions before executing the next generation. Moreover, the effect of the common controlling parameters of the algorithm i.e. population size, number of generations and elite-size on the performance of the algorithm were also investigated by considering different population sizes, number of generations and elite sizes.

The working principles of the basic TLBO model can be explained into two parts, "Teacher phase" and "Learner phase" as described below.

Teacher Phase

Teacher is usually considered as highly qualified among the group and in this phase teacher imparts his knowledge in between the learners. A good teacher may bring his/ her learners up to his/ her level in terms of knowledge but actual in practise it is not possible and a teacher can increase mean of the class room M_1 to any other value M_2 which is better than M_1depending on his or her capability.

Considered M_j be the mean and T_i be the teacher at any iteration i. Now T_i will try to improve existing mean M_j towards it so the new mean will be T_i designated as M_{new} and the difference between the existing mean and new mean is given by:

$$Differene\_Mean_i = r_i\left(M_{new} - T_f M_j\right) \tag{3.4}$$

Here T_f is the teaching factor which decides the value of mean to be changed, and r_i is the random number in the range [0, 1]. Value of T_f can be either 1 or 2 which is a heuristic step and it is decided randomly with equal probability as:

$$T_f = round[1 + rand(0,1)\{2-1\}] \tag{3.5}$$

This difference modifies the existing solution according to the following expression:

$$X_{new,i} = X_{old,i} + Differenc\_Mean_i \tag{3.6}$$

Learner Phase

In this phase, communication among the learners and also with teacher led to increase their knowledge. A learner can enhance their knowledge if the other learner has more knowledge than him or her. Considering a population size of n, the learning phenomenon of this phase is expressed below.

At any iteration i, considering two different learners X_i and X_j where $i \neq j$

$$\begin{aligned} X_{new,i} &= X_{old,i} + r_i\left(X_i - X_j\right) \text{ if } f\left(X_i\right) < f\left(X_j\right) \\ X_{new,i} &= X_{old,i} + r_i\left(X_j - X_i\right) \text{ if } f\left(X_j\right) < f\left(X_i\right) \end{aligned} \tag{3.7}$$

Accept X_{new} if it gives better function value.

The flow diagram of TLBO algorithm has been presented in Fig. 3.1.

3.1.6 Results and Discussions

3.1.6.1 Modelling of MRR, Cutting Force (CF) and Surface Roughness (SR)

Based on (Eq. 3.3), the effects of the process variables on corresponding responses (MRR, CF and SR) have been evaluated by computing the values of various coefficients using MINITAB software package and exploring experimental data collected from Table 3.3. The mathematical relationship between the cutting force (CF) and manufacturing parameters can be expressed as follows:

$$CF(Z_1) = 5.01388 * X_1^{0.00148721} * X_2^{0.459238} * X_3^{0.831053} * X_4^{0.184602} \tag{3.8}$$

Here: CF = cutting force in kgf.

Also, the mathematical correlation between surface roughness (SR) and the corresponding machining process has been developed as follows:

$$SR(Z_2) = 0.030679 * X_1^{0.102744} * X_2^{-0.961585} * X_3^{0.125134} X_4^{0.562925} \tag{3.9}$$

Here: SR = surface roughness (R_a) in µm

The mathematical relationship for correlating the material removal rate (MRR) and the machining process parameters considered can be expressed as follows:

$$MRR(Z_3) = 8.778276 * X_1^{0.399957} * X_2^{-1.10765} * X_3^{1.70906} * X_4^{-0.0735473} \tag{3.10}$$

Here: MRR = material removal rate in mm^3/min.

3.1.6.2 Model Adequacy Test for MRR, Cutting Force and Surface Roughness

An ANOVA (analysis of Variance) and P-value test (represented in Table 3.4) has been performed to justify the validation of the developed mathematical models. The calculated P-value for MRR, cutting force and surface roughness appear less than 0.05, stating insignificance of the lack of fit. Hence, the developed mathematical models that link the various machining parameters with for MRR, cutting force and surface roughness can be adequately represented through non-linear regression model.

In first phase of this work, objective functions have been derived (for individual response features: MRR, cutting force, surface roughness) using non-linear regression analysis. Those mathematical models have been represented as a function of input parameters.

These objective functions have been optimized individually using TLBO algorithm in the selected parametric search space. Now, in deriving objective functions, model adequacy is an important factor. Though, in the present work, the Box-Behnken design of experiment has been used and the computation has been carried out in a statistical software package MINITAB; the second order quadratic models thus generated through MINITAB on exploration of experimental data appeared inadequate. Hence, using non-linear regression analysis objective functions of individual responses have been derived and the model adequacy has been verified. Though the objective functions seem not to be highly nonlinear; still, model statistics says that all are adequate (Table 3.4). Thus, these models have been considered here and further optimized using TLBO.

3.1.6.3 Optimization of CFRP Machining Parameters

It is quite difficult to machine CFRP composites due to its anisotropic nature. The major problems encountered during the machining of these composites are fibre pull out, delamination, stress concentration; swelling, splintering and micro- cracking etc. resulting in decrease in the composite performance and strength. It is very difficult to understand effects of process parameters such as spindle speed, feed rate and depth of cut in machining of composites due to their nonlinear behaviour. In turning operation, MRR can be interpreted in terms of productivity; whereas, surface roughness defines the quality of the product. Cutting forces are mainly responsible for the tool wear which ultimately reduce the quality of tool. Hence, it is essential to understand machinability aspects of these composites. This paper, therefore, developed mathematical model for MRR, surface roughness and cutting force to study the effect of process parameters in turning of CFRP composites. Optimization of process parameters is vital to achieve compatible balance between quality and productivity which include high production rate with reduced cost as well as to maintain good surface finish and dimensional accuracy. During machining, the researchers aim at obtaining a global optimal machining condition but the objective function may be multimodal i.e. have many local minimum or maximum. It is very difficult to solve such type of problems by conventional methods of optimization such as gradient search methods. Hence, meta-heuristic techniques such as GA, PSO, SA, ABC, TLBO etc. are introduced to provide solutions near to the global optimum within reasonable time and less computational effort.

This work focuses on application of TLBO to evaluate optimal solution in turning of CFRP composites. As compared to other meta-heuristic techniques such as GA, PSO, SA, this methods require less parameters (i.e. only 3) i.e. to be adjusted for determination of optimal solution which reduces the computational efforts.

The TLBO algorithm discussed above uses (Eq. 3.8-3.10), as objective functions to minimize the cutting force, surface roughness and maximize the material removal rate, respectively. The parameter bounds have been listed as follows:

$220 \leq X_1 \leq 860$ *Spindle speed*

$0.06 \leq X_2 \leq 0.08$ *Feed rate*

$0.9 \leq X_3 \leq 1.5$ *Depth of cut*

$45 \leq X_4 \leq 90$ *Fiber orientation angle*

Both single objective optimization as well as multi-objective optimization has been performed and the results obtained, thereof, have been furnished in Table 3.5. For multi-objective optimization equal weightage has been assigned for the each performance characteristics.

For multi-objective optimization, decision variables and variable bounds are the same as specified for the single objective optimization. The normalized combined objective function (Z) has been formulated by considering different weightages to all objectives as given by the following equation:

$$Z = \frac{W_1 * Z_1}{Z_{1\min}} + \frac{W_2 * Z_2}{Z_{2\min}} - \frac{W_3 Z_3}{Z_{3maz}} \quad (3.11)$$

$Z_{1\min}$ = Minimum value of cutting force (2.5686 kgf) obtained when the single-objective optimization problem considering only cutting force as an objective.

$Z_{2\min}$ = Minimum value of surface roughness (5.0956 µm) obtained when the single-objective optimization problem considering only surface roughness as an objective.

$Z_{3\max}$ = Maximum value of material removal rate (4465 mm^3/min.) obtained when the single-objective optimization problem considering only material removal rate as an objective.

W_1, W_2 and W_3 = Weight assigned to the objective functions Z_1, Z_2 and Z_3 respectively.

The TLBO convergence plots for optimizing cutting force, MRR and surface roughness have been depicted in Figs. 3.2-3.4, respectively. Similarly, for multi-objective optimization, the TLBO convergence plot for the combined objective function (Z) has been furnished in Fig. 3.5.

The normalized combined objective function has been found to be minimal at 0.6544. The optimal parametric combination for the multi-objective optimization has been used to calculate the cutting force, surface roughness and material removal rate which have been tabulated in Table 3.6. For generating the optimal setting, population size= 10, Maximum Number of generation= 20 and teaching factor =2 has been taken in consideration.

Based on the work by (Rao et al. 2011), it has been observed that initial parameters in TLBO are taken for consideration set up are population size maximum number of generations, and teaching factor. The population size is varied from 10 to 50 and maximum number of generation is taken to 20 to 100 for aforesaid mathematical model. After several number of computation, the parameters are set as population size = 10, maximum number of generations = 20, and teaching factor = 2 to obtain optimal solution.

The performance of TLBO has also been compared with that of GA (Genetic Algorithm). Results have been highlighted in Table 3.7. Convergence curves for the fitness function of cutting force, surface roughness, MRR and Mutli-objective function (Z) have been depicted in Figs. 3.6-3.9, respectively.

The fitness value for cutting force, surface roughness, MRR and for combined objective function (Z) 2.5686, 5.0956, 4465, and 0.6544, respectively, by using TLBO; whereas, fitness value for cutting force, surface roughness, MRR and for combined function (Z) obtained as 2.6020, 6.3446, 4366.5277, and 0.680306, respectively by using GA as shown in Table 3.7; while considering initial parameter settings of GA as shown in Table 3.8. It has been observed that TLBO provides better result as compared to GA with less number of initial adjusting algorithmic parameters.

At the end of this computational part of the study, error analysis has also been conducted. It has been found that the percentage error between predicted and experimental data is quite acceptable and satisfactory.

Fig. 3.10 and Fig. 3.11 show the micrograph of the work piece before and after turning operation of CFRP composites by scanning electron microscope (JEOL JSM 6480LV). It has been noticed that the fibers were cut in huge amount and stick on the surface of the machined material which lead to increase in surface roughness values.

Commonly used meta-heuristics such as GA, PSO, SA, ACO etc. are preferred these days over traditional optimization methods; because, the meta-heuristics have better exploration and exploitation capability and generate near optimal solution. The major drawback of trapping at local optimum of traditional optimization methods has been solved to a large extent by use of meta-heuristics. GA and SA not only require high computational time but also require more algorithmic parameters to be adjusted; whereas, PSO causes premature convergence. The ACO and ABC simulate complex natural process. TLBO on the other hand is simple and easy to understand as it mimics simple phenomenon i.e. interaction among the teacher and student in class room study. Also, the initial setting parameters for TLBO are only three; whereas, GA, ACO, PSO etc. need more than five parameters to be adjusted requiring more computational time.

This work attempts of explore basic TLBO algorithm towards determining optimal machining parameters settings in view of different process performance yields in the context of machining (turning) of CFRP composites. The work initially attempts to derive optimal settings considering individual response features like MRR, R_a and cutting force, respectively. In later phase, aforesaid individual response features have been aggregated to obtain a combined objective function (Z) and finally optimized using TLBO. Results of TLBO have also been compared with GA; showed better performance for TLBO. In basic TLBO, there exists a teacher in a classroom whose knowledge is shared amongst the students (teaching-learning). Further, basic TLBO has been improved in which not only teacher supplies knowledge; students also learns themselves. More recent advancements of TLBO assumes involvement of more than one teacher (along with students) in knowledge sharing; which is termed as Multi-objective TLBO (Patel et al. 2014a, b; Zou et al., 2013). Multi-objective TLBO is the latest version of TLBO and not fully developed and available in published literature resource. Definitely, its performance is expected to be better as compared to basic TLBO. Hence, the application potential of multi-objective TLBO in optimizing process responses in the context of CFRP machining needs to be examined in future.

3.1.7 Concluding Remarks

The present research focuses on investigating the influences of process parameters (parametric appraisal) in turning of CFRP composites along with optimization of machining parameters (process variables). Nonlinear regression model has been developed for analyzing the effect of process parameters such as spindle speed, feed rate, depth of cut and fiber orientation angle. Material removal rate, cutting force and surface roughness have been considered for evaluation of machining performance characteristics. In the present study, ANOVA and P-value test have been performed to justify the validation of the developed mathematical models (objective functions). The study also illustrates the feasibility of the relatively new optimization algorithm i.e. TLBO which needs less computational effort for solving constrained and unconstrained problems for obtaining the optimal solution. This newly adopted technique TLBO requires very small population size and less number of iterations in order to get optimal parametric combination which can efficiently be applied further for parametric appraisal in any machining processes which involve multiple response features related with each other.

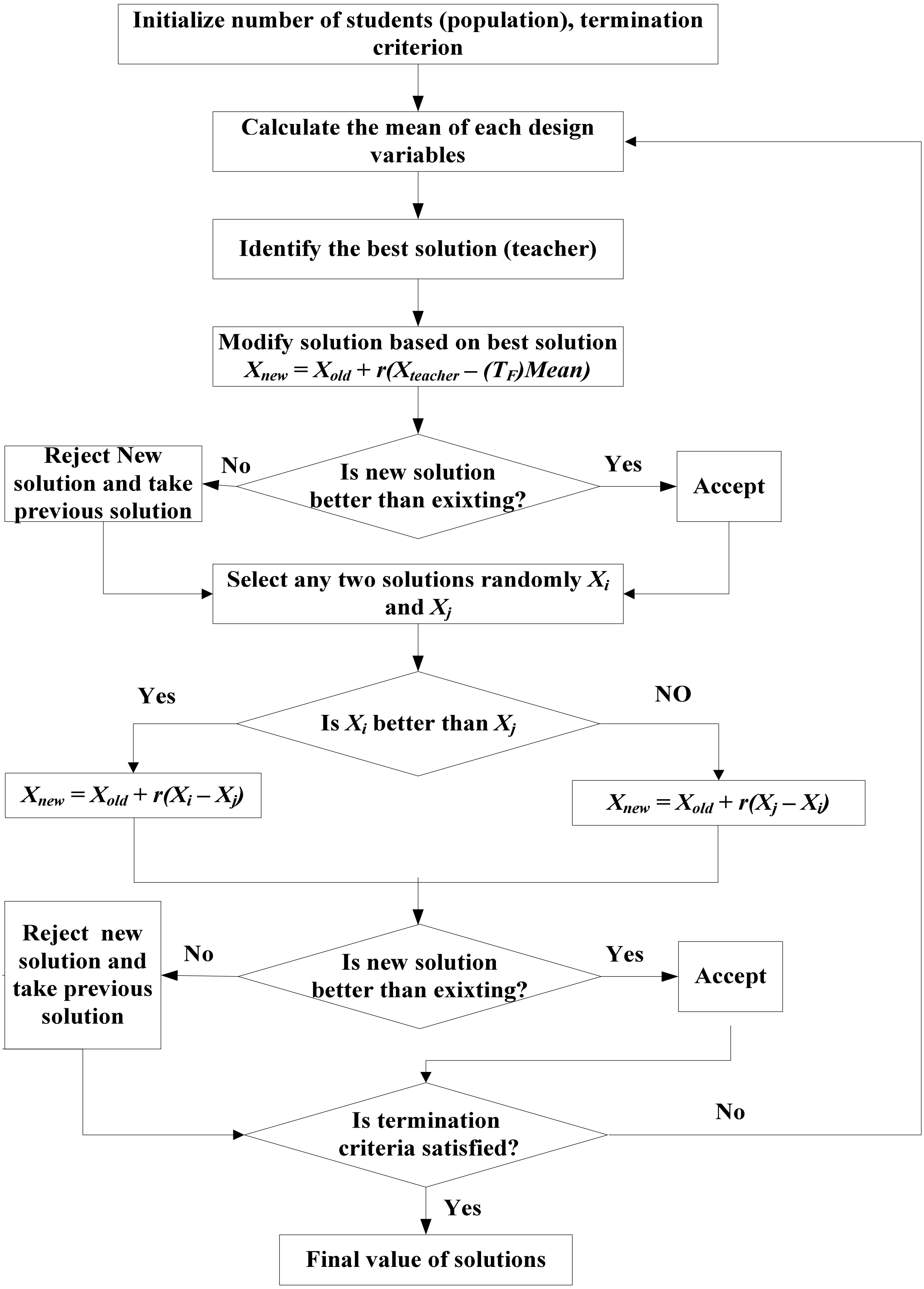


Fig. 3.1: Flow diagram of TLBO algorithm

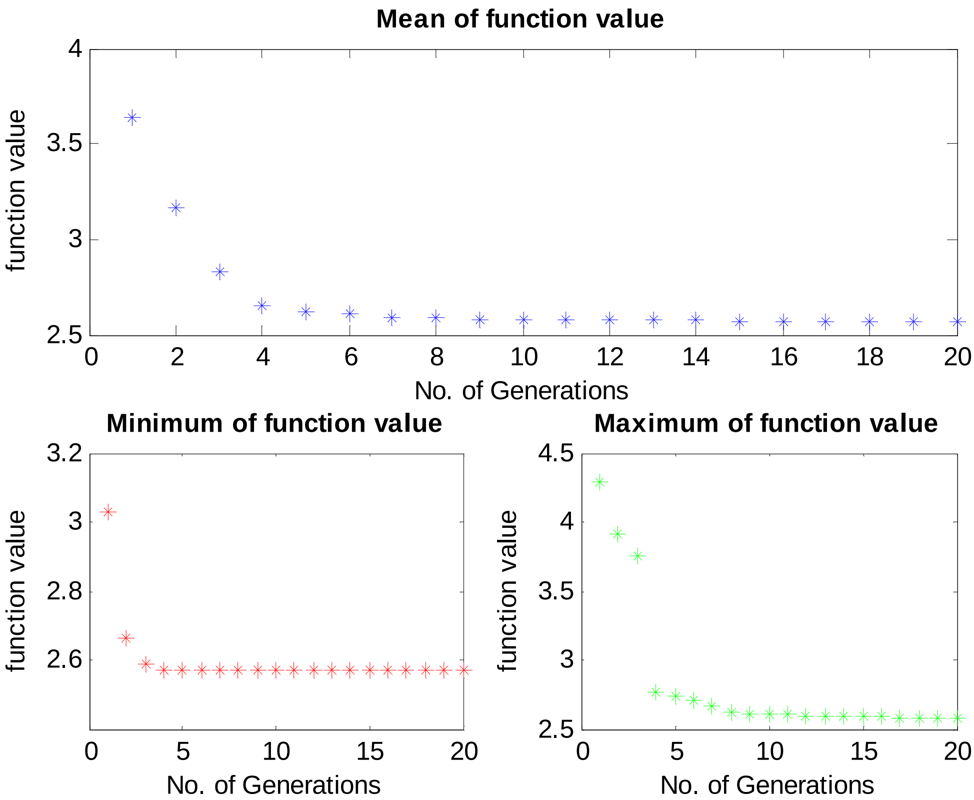


Fig. 3.2: Convergence plot for optimizing cutting force using TLBO

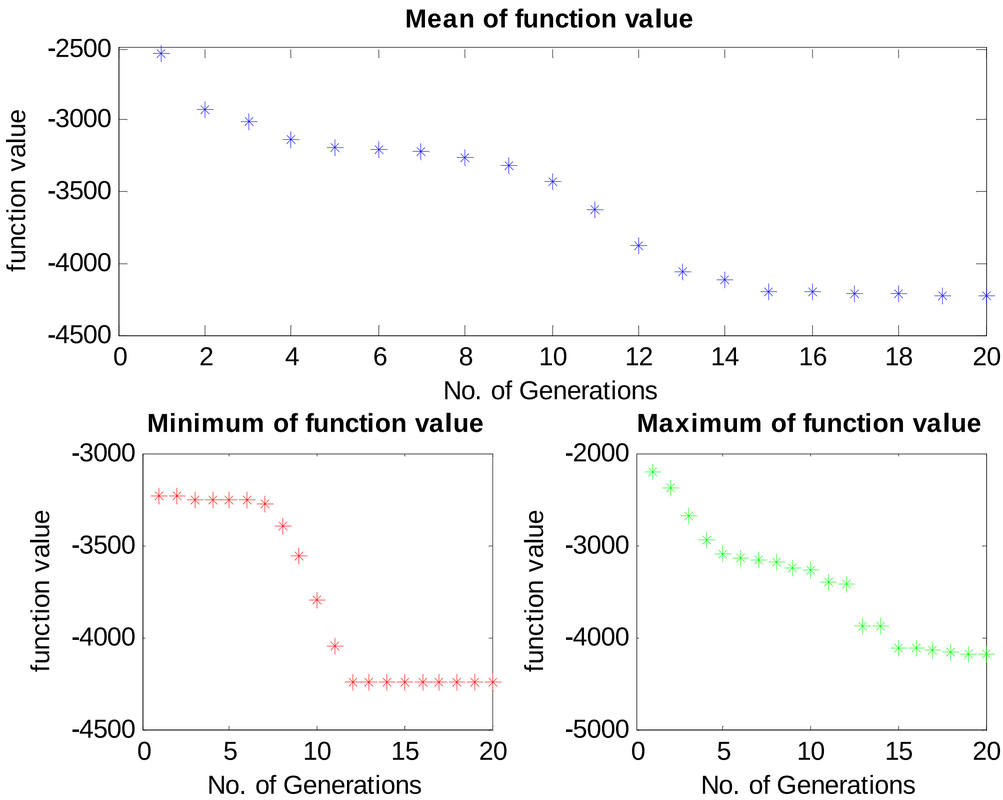


Fig. 3.3: Convergence plot for optimizing MRR using TLBO

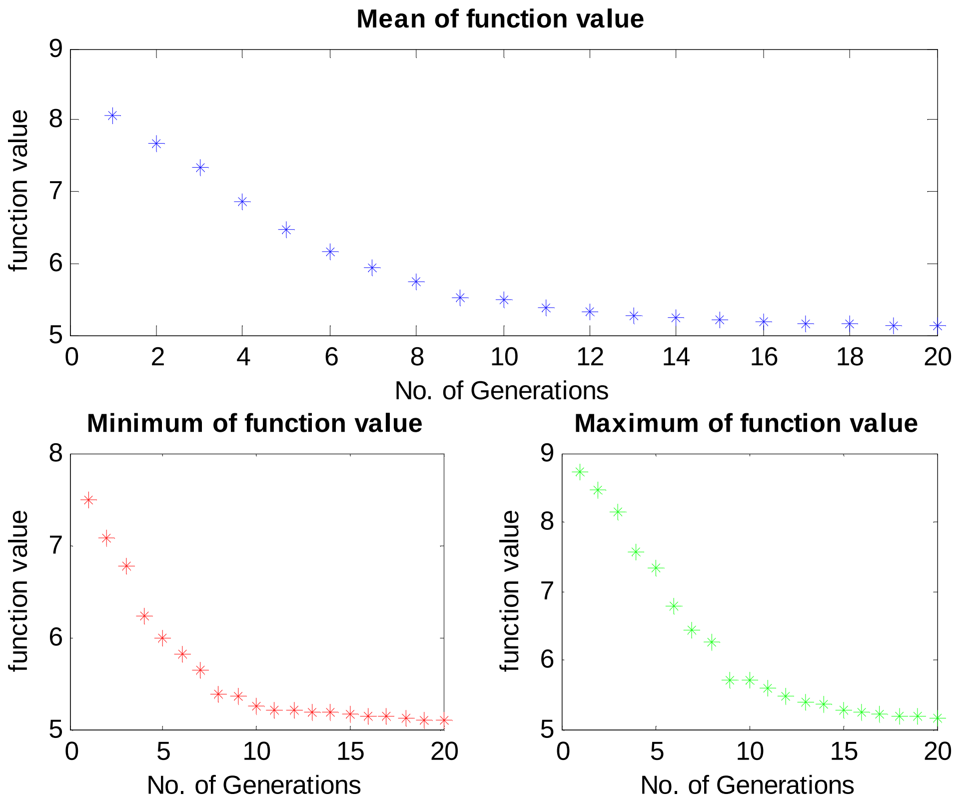


Fig. 3.4: Convergence plot for optimizing surface roughness using TLBO

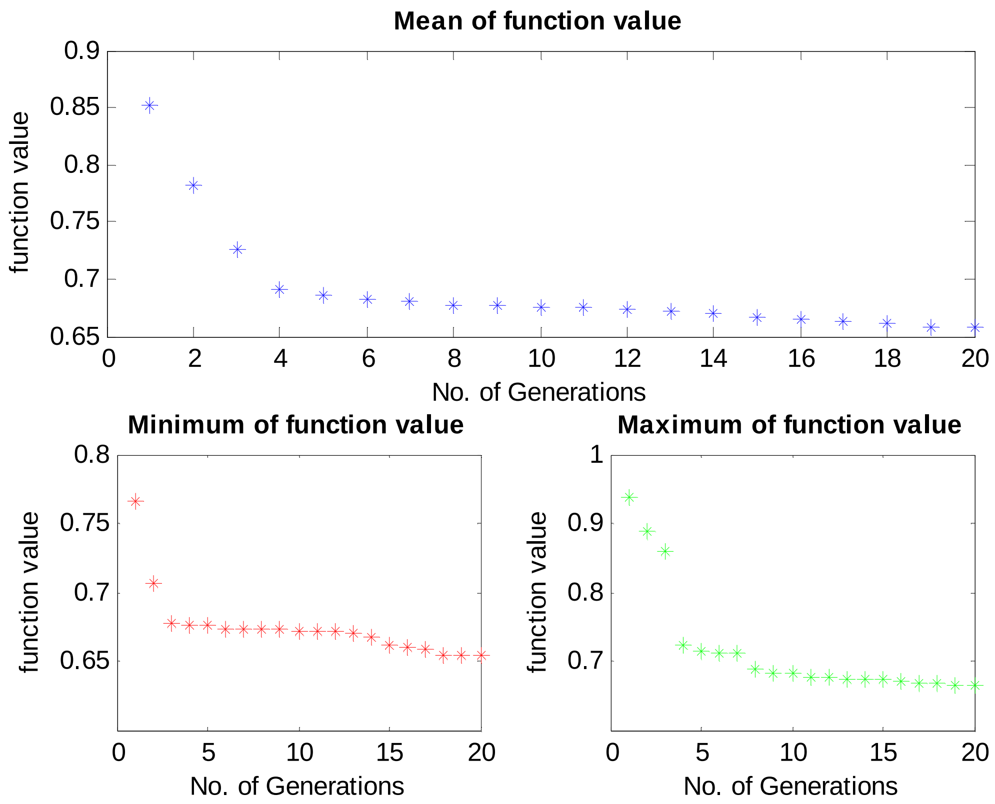


Fig. 3.5: Convergence plot for optimizing multi-objective combined function using TLBO

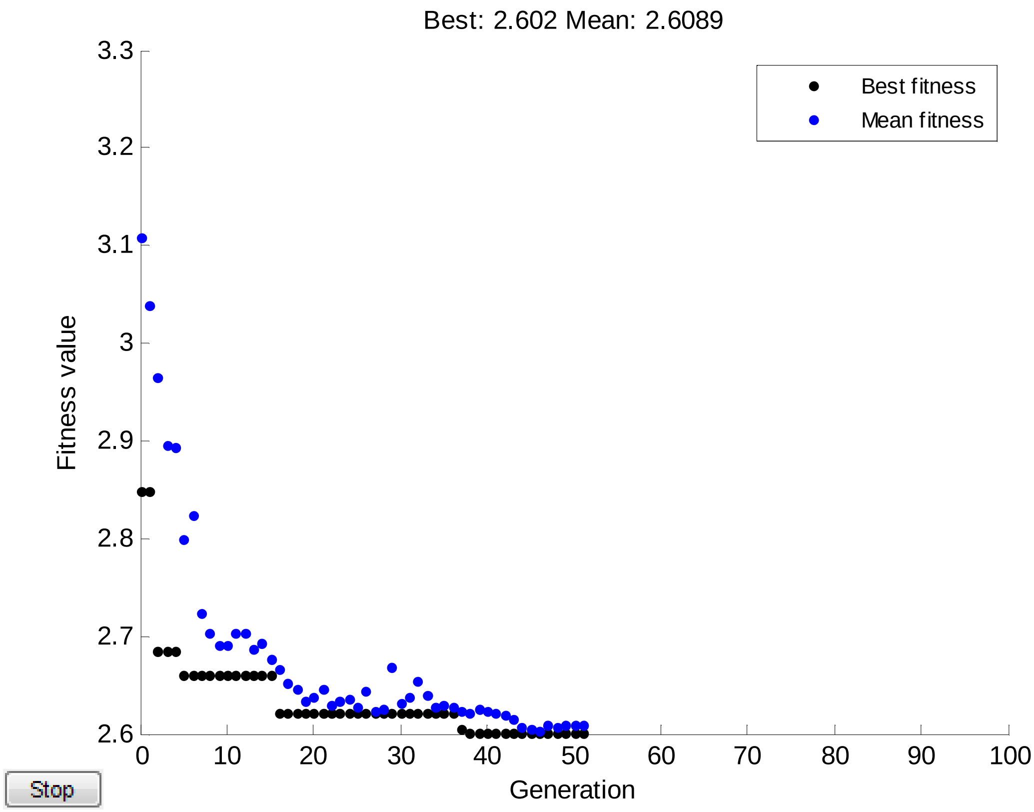


Fig. 3.6: Convergence curve of fitness function of cutting force using GA

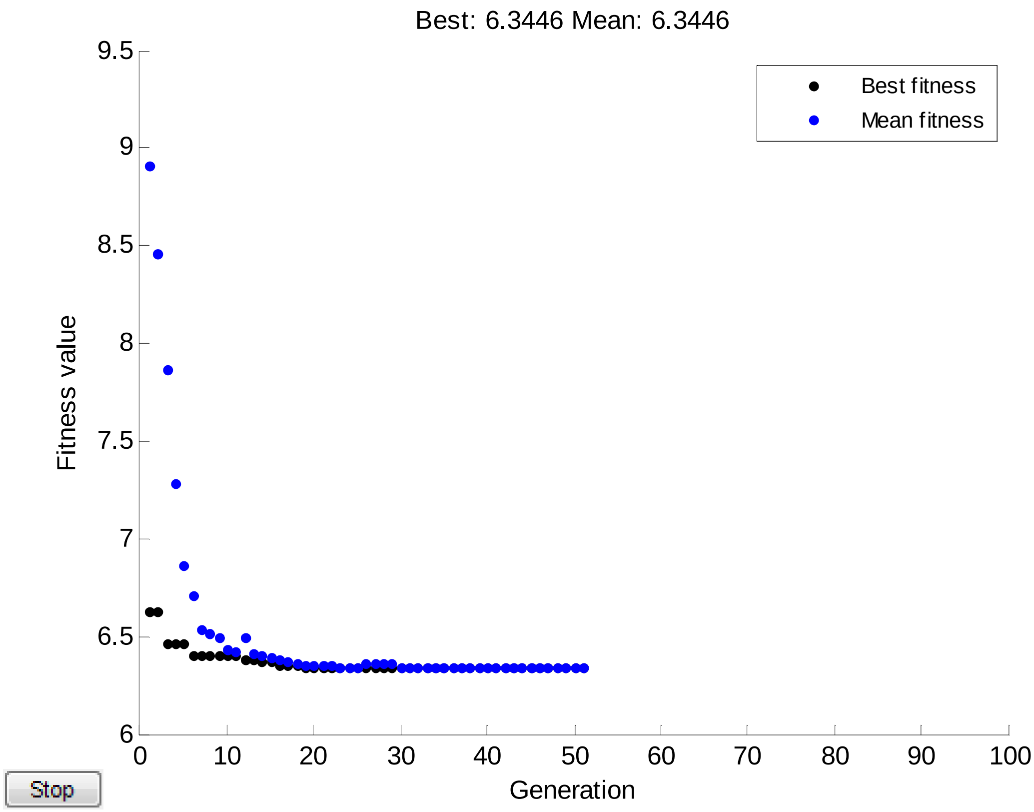


Fig. 3.7: Convergence curve of fitness function of surface roughness using GA

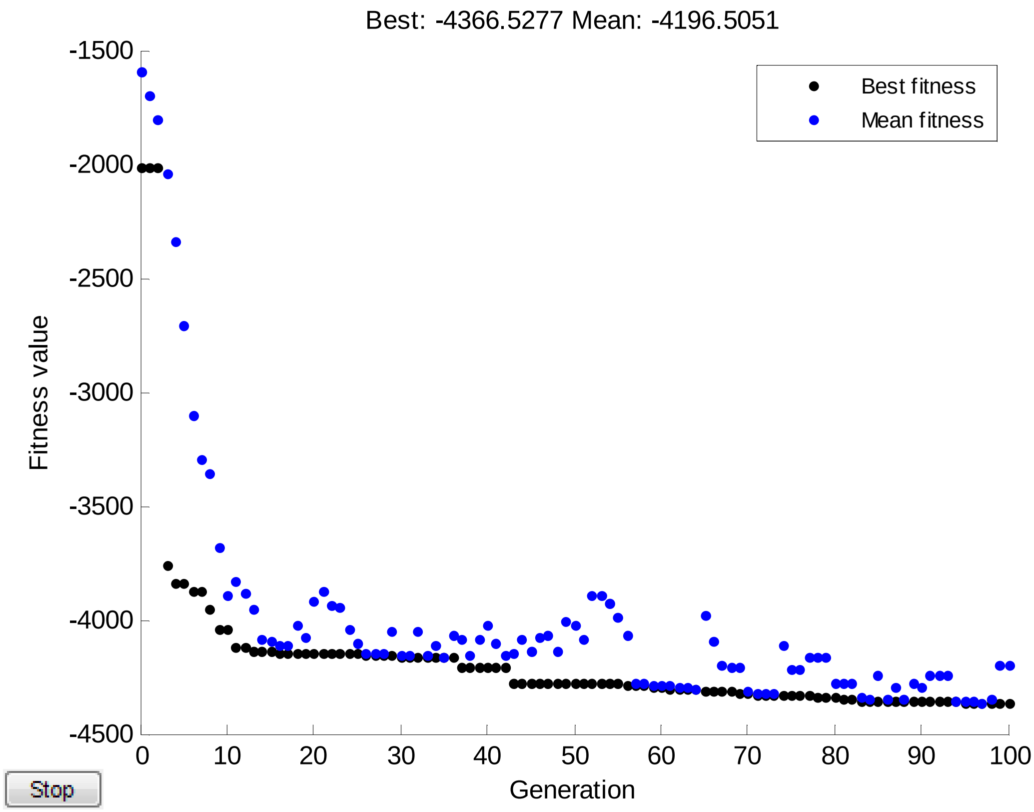


Fig. 3.8: Convergence curve of fitness function of MRR using GA

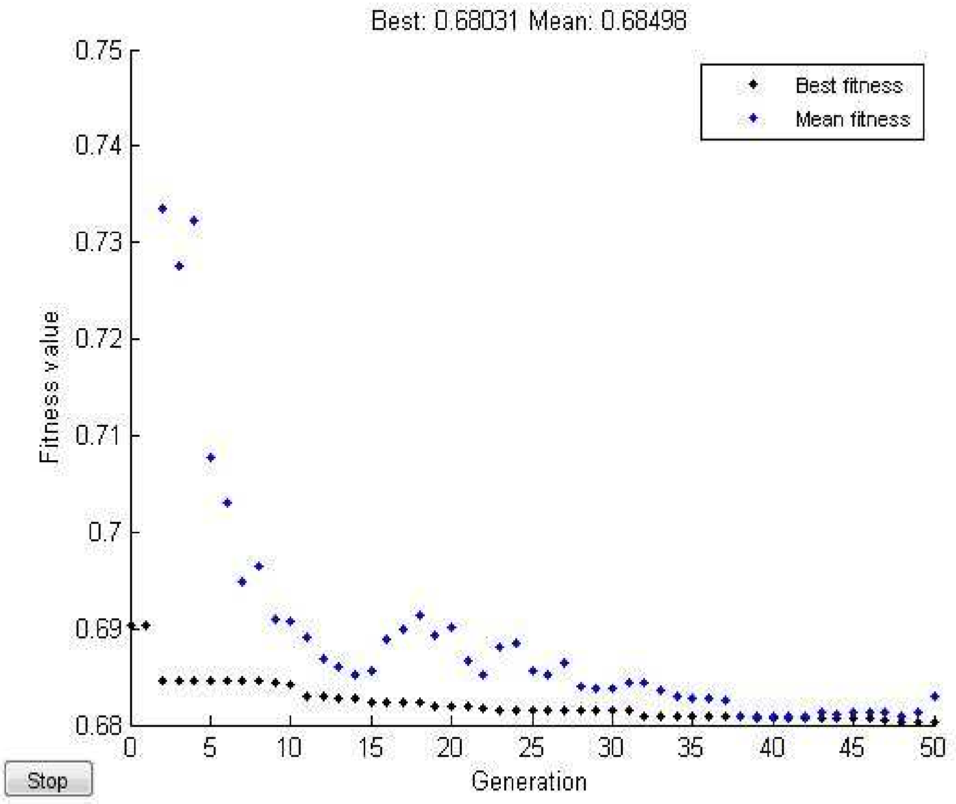


Fig. 3.9: Convergene curve of fitness function of Z using GA

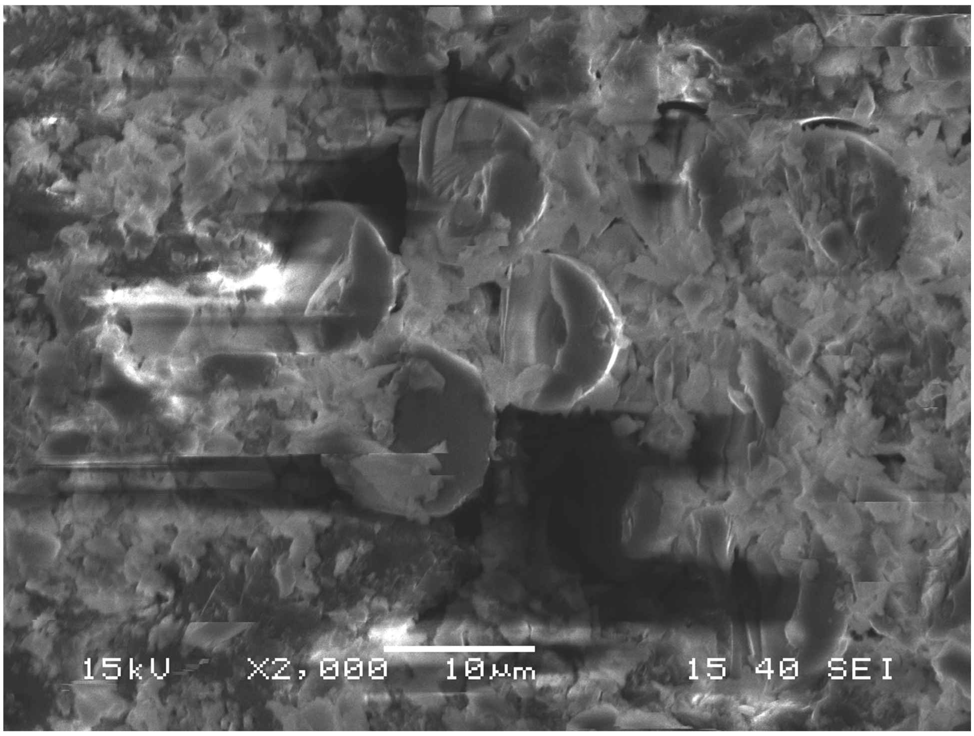


Fig. 3.10: SEM image of CFRP composite before machining

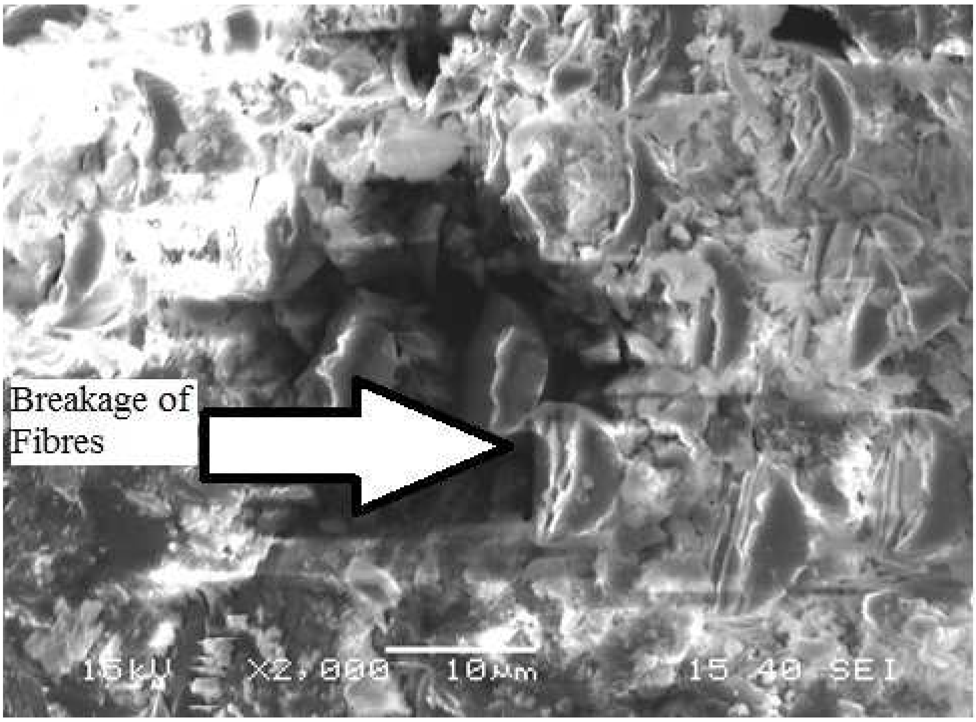


Fig. 3.11: SEM image of CFRP composite after machining

Table 3.1: Application of evolutionary techniques in machining parameters optimization

Machining process(s)	Evolutionary Techniques
Drilling	GA (Jayabal and Natarajan, 2010; Kilickap et al., 2011), SA (Satishkumar and Asokan, 2008), PSO (Gaitonde and Karnik, 2012), HS (Chatterjee et al., 2014)
Milling	GA (Xu et al., 2010); SA, PSO (Li et al., 2008)
Turning	GA (Duran et al., 2008; Prasad et al., 2007), SA (Kolahan and Khajavi, 2010-2), PSO (Bharathi and Baskar, 2011; Xi and Liao, 2009), ACO (Cus et al., 2009; Vijayakumar et al., 2003)
End milling	GA (Palanisamy et al., 2007; Parent et al., 2007), SA (Zain et al., 2010), PSO (Farahnakian et al., 2011), ACO (Kadirgama et al., 2010)
EDM	GA (Maji and Pratihar, 2010; Gao et al., 2008; Mandal et al., 2007), SA (Yang et.al., 2009)
ECM	GA (Jain and Jain, 2007), PSO (Rao et al., 2008)
WEDM	GA (Mahapatra and Patnaik, 2007), SA (Chen et al., 2010), TLBO (Rao and Kalyankar, 2013)

Table 3.2: Process parameters and selected domain of experiment

Sl. No.	Process parameters	Notation	Unit	Level 1	Level 2	Level 3
1	Spindle Speed	X_1	[RPM]	220	540	860
2	Feed rate	X_2	[mm/rev]	0.06	0.07	0.08
3	Depth of cut	X_3	[mm]	0.9	1.2	1.5
4	Fiber orientation angle	X_4	[degree]	45	60	90

Table 3.3: Experimental plan and collected responses based on Box-Behnken design of experiment

StdOrder	RunOrder	PtType	Blocks	Design of experiment				Experimental data		
				X_1 [RPM]	X_2 [mm/rev]	X_3 [mm]	X_4 [Degree]	CF [Kgf]	SR [µm]	MRR [mm^3/min]
1	1	2	1	220	0.06	1.2	67.5	2.98665	10.3503	2092.91
2	2	2	1	860	0.06	1.2	67.5	6.36400	11.9190	2745.34
3	3	2	1	220	0.08	1.2	67.5	6.57421	5.9303	1346.40
4	4	2	1	860	0.08	1.2	67.5	3.60461	10.9967	1999.60
5	5	2	1	540	0.07	0.9	45.0	2.09747	4.3910	913.25
6	6	2	1	540	0.07	1.5	45.0	3.67340	6.2070	2159.57
7	7	2	1	540	0.07	0.9	90.0	2.27557	10.1457	1466.34
8	8	2	1	540	0.07	1.5	90.0	4.63657	9.3103	2772.78
9	9	2	1	220	0.07	1.2	45.0	4.07638	7.2720	1267.89
10	10	2	1	860	0.07	1.2	45.0	4.34888	6.0723	3945.88
11	11	2	1	220	0.07	1.2	90.0	4.10526	8.1947	1639.67
12	12	2	1	860	0.07	1.2	90.0	4.37873	12.3450	3159.37
13	13	2	1	540	0.06	0.9	67.5	2.56994	13.8760	717.85
14	14	2	1	540	0.08	0.9	67.5	3.95387	6.0270	1079.78
15	15	2	1	540	0.06	1.5	67.5	5.93700	7.5627	4079.18
16	16	2	1	540	0.08	1.5	67.5	5.06496	11.8360	2172.90
17	17	2	1	220	0.07	0.9	67.5	5.04614	9.6480	1326.73
18	18	2	1	860	0.07	0.9	67.5	5.03644	9.0707	1852.96
19	19	2	1	220	0.07	1.5	67.5	4.35244	8.2830	1789.21
20	20	2	1	860	0.07	1.5	67.5	8.41568	12.2577	4585.34
21	21	2	1	540	0.06	1.2	45.0	2.19941	7.5560	2239.55
22	22	2	1	540	0.08	1.2	45.0	2.66177	7.5573	6345.67
23	23	2	1	540	0.06	1.2	90.0	2.45540	11.1540	6589.38
24	24	2	1	540	0.08	1.2	90.0	2.68918	6.3293	973.14
25	25	0	1	540	0.07	1.2	67.5	2.15395	6.2170	1421.76
26	26	0	1	540	0.07	1.2	67.5	3.99241	5.2920	1067.34
27	27	0	1	540	0.07	1.2	67.5	2.10471	4.0750	1239.75

Table 3.4: ANOVA

Source	DOF	Sum of square of source			Mean sum of square of source			P-value		
		MRR	CF	SR	MRR	CF	SR	MRR	CF	SR
Linear	4	16893412	12.8869	58.507	1954954	0.6461	25.0754	0.047	0.038	0.000
Square	4	10020906	31.7250	56.850	2505227	7.9312	14.2124	0.051	0.000	0.000
Interaction	6	26541702	15.6577	59.712	4423617	2.6096	9.9520	0.005	0.005	0.000
Lack of fit	10	9252569	3.0599	9.808	925257	0.3060	0.9808	0.053	0.940	0.652
Pure error	2	62821	2.3152	2.308	31411	1.1576	1.1541			
Total	26	62771410	65.6448	187.185						

Table 3.5: Results of single objective and multi-objective optimization

Optimization for	**X_1**	**X_2**	**X_3**	**X_4**	**Z**
Minimizing the cutting force	220	0.06	0.9	45	2.5686
Minimizing the surface roughness	220	0.08	0.9	45	5.0956
Maximizing the MRR	860	0.06	1.5	45	4465
Multi-objective optimization	220	0.08	0.9	45	0.6544

Table 3.6: Results of different output response at optimal parametric combination

X_1	**X_2**	**X_3**	**X_4**	**Z**	Cutting force	Surface roughness	MRR
220	0.08	0.9	45	0.6544	2.9314	5.0956	2786.1

Table 3.7: Comparison of performance between TLBO and GA

Algorithm	Responses	Optimal Parametric Combination				Fitness value
		Spindle speed	Feed Rate	Depth of cut	Fibre Orientation	
Genetic Algorithm	Cutting Force	369.2627	0.0601	0.9	50.9949	2.6020
	Surface Roughness	605.00	0.0799	0.9	45	6.3446
	MRR	857.8578	0.0606	1.4952	47.1465	4366.5277
	Z	220.0575	0.08	0.903388	49.38967	0.680306
TLBO	Cutting Force	220	0.06	0.9	45	2.5686
	Surface Roughness	220	0.08	0.9	45	5.0956
	MRR	860	0.06	1.5	45	4465
	Z	220	0.08	0.9	45	0.6544

Table 3.8: Initial parameters setting for GA

Tuning Parameters	Value
Population size=	70
Maximum no. of generation=	100
Selection function=	Stochastic function
Elite Count=	2
Crossover fraction=	0.8
Crossover function=	Scattered
Mutation factor=	0.2
Mutation function=	constraint dependent

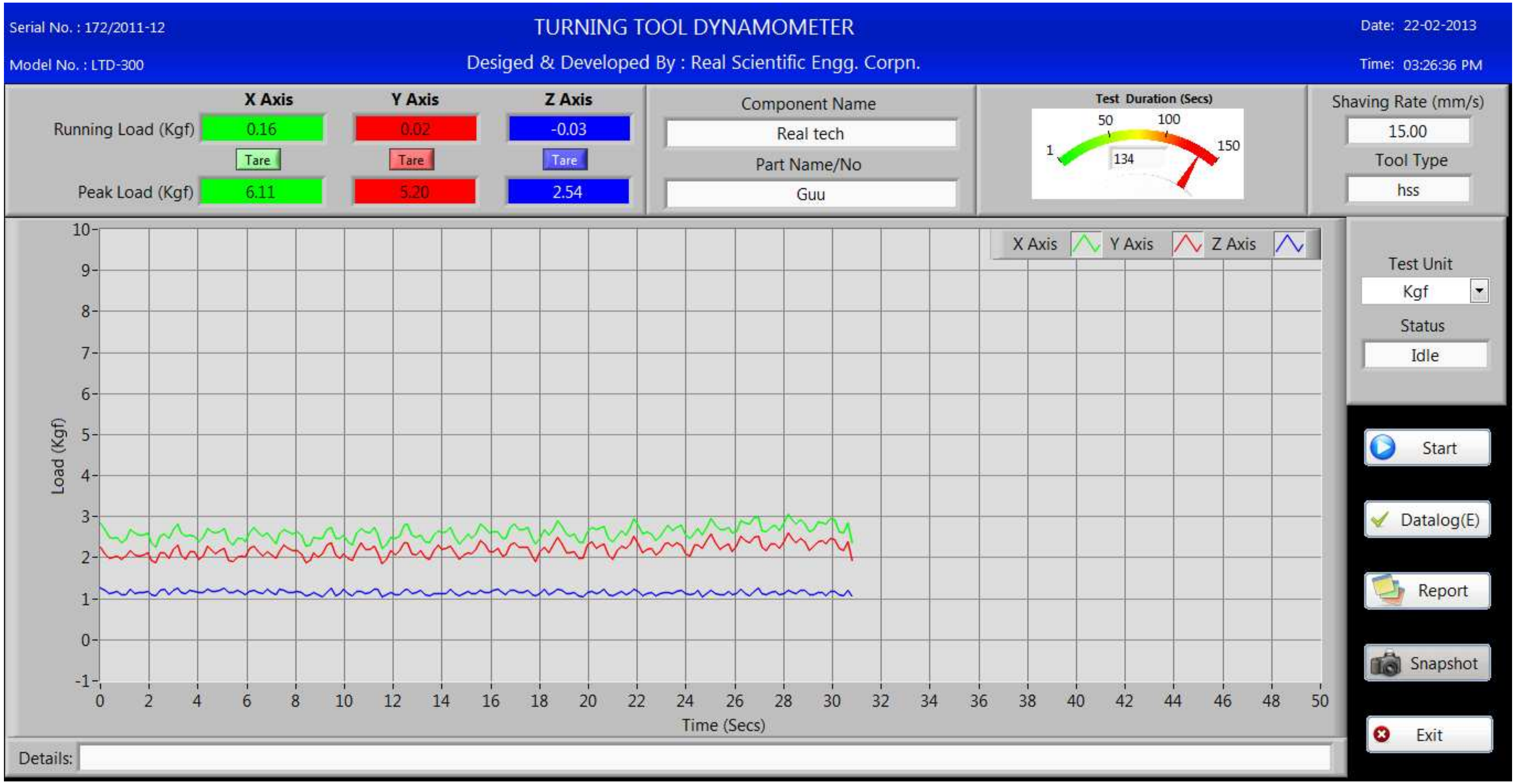


Fig. 3.12: Determination of cutting forces using turning tool dynamometer (For Sample No. 20)

3.2 Application of Imperialist Competitive Algorithm (ICA) for Selection of Optimal Machining Condition during Turning of CFRP (Epoxy) Composites

3.2.1 Coverage

With the widespread application of Carbon Fiber Reinforced Polymer (CFRP) composites mostly in defense, aerospace applications; machining of those materials has become a major concern today. As machining and machinability aspects of those composites differ from conventional metals; proper understanding of process behavior followed by identifying the favorable machining environment (optimal setting of process parameters) is of utmost important. The present work highlights application of nonlinear regression and fuzzy logic in combination with the Imperialist Competitive Algorithm (ICA) for selection of optimal process parameters setting during machining (turning) of carbon fiber reinforced (epoxy) composites. Experiments have been carried out in consideration with cutting speed (spindle speed), feed and depth of cut as process control parameters; whereas, Material Removal Rate (MRR), roughness average of the machined surface and cutting force have been treated as machining performance characteristics. Attempt has been made to identify best setting of process parameters for optimizing aforesaid output responses. Results of fuzzy based ICA approach have been compared with Genetic Algorithm (GA) as well as traditional Taguchi's optimization philosophy. Application potential of fuzzy embedded ICA towards optimizing machining performance yields has been demonstrated in the present experimental research.

3.2.2 Problem Definition

Literature is found quite vast in addressing machining and machinability aspects of glass fiber based polymer composites. Extensive research has been carried out by pioneers towards process modelling, parametric appraisal as well as optimization of the machining performance features (Deshpande et al., 2014; Latha and Senthilkumar, 2010; Palanikumar, 2011; Zheng et al., 2012; Krishnamoorthy et al., 2009; Palanikumar et al., 2008; Mata et al., 2010; Palanikumar et al., 2013; Palanikumar et al., 2006; Panda and Mahapatra, 2011; Mata et al., 2009; Palanikumar et al., 2008).

Taguchi based optimization approaches (desirability function, utility theory, grey relation analysis, TOPSIS) (Puhan et al., 2013; Caydas and Hascalık, 2008; Datta et al., 2014; Sahu et al., 2013; Ahilan et al., 2010; Kumar and Khamba, 2010; Rajmohan et al., 2013) are based on some assumptions and these techniques possess few limitations. The assumptions of aforesaid optimization approaches appear unrealistic in practice. Existence of response correlation and assignment of response priority weight seem to be the main problems that a decision-maker is likely to face. Therefore, these techniques may perform well in theory, but may fail in real world complex situations. In real manufacturing process, several conflicting responses (i.e. output characteristics) may affect the optimal solution because of the nonlinear characteristics of inputs with respect to the output responses. The objective function may be multimodal (i.e. more than one local minimum or maximum); but the main aim is to evaluate the global optimal values within the given search space/domain. Traditional methods are found inefficient to handle these type problems; hence, advanced optimization algorithms are developed to seek for the feasible solution as they intend to find solution near to global optimum in lesser time and with lesser computational effort.

Nowadays, several evolutionary techniques are being used to solve different optimization problems in various fields such as industrial planning, scheduling, decision making and pattern recognition etc. They basically follow nature based optimization ideology. The most common evolutionary method is Genetic Algorithm (Al-Aomar, 2006; Mondal et al., 2007; Sahoo, 2011; Kumar et al., 2014) which is based on principles of genetics and evolution, and mimics the reproduction behaviour observed in biological populations. Particle Swarm Optimization (PSO) (He et al., 2004; Haq et al., 2006; Hsu et al., 2015) technique is a heuristic technique which is basically inspired by social behaviour of animals such as fish schooling or birds flocking; whereas, Ant Colony Optimisation (ACO) (Vijayakumar et al., 2003) is motivated by foraging behaviour of real life ant colonies. Simulated Annealing (SA) is the process in which a substance is virtually heated above its melting point and then slowly cooled down to minimizes the energy distribution. More information on algorithm based optimization approaches could be found in (Cheheltania and Ebadzadehb, 2012; Alaghebandha and Hajipour, 2015; Alazzam and Lewis, 2013; Chandrasekaran et al., 2010).

Literature depicts that very limited work has been attempted to explore evolutionary algorithms for evaluating the optimal parametric combination in machining of composite materials. Hence, this work aims to focus on evaluating optimal machining condition for turning of CFRP (epoxy) composites by exploring a relatively new meta-heuristic algorithm i.e. Imperialist Competitive Algorithm (ICA) (as proposed by Atashpaz-Gargari and Lucas, 2007). This algorithm is based on the socio-political relationship amongst the countries to generate the said optimal combination. The entire work has been conducted in four phases (Talatahari et al., 2012; Pourbaba et al., 2013; Ghanizadeh et al., 2011; Mitras and Sultan, 2013):

Experiments have been conducted according to Taguchi's orthogonal array design by varying controllable process parameters (viz. spindle speed, feed rate and depth of cut) in order to evaluate different performance characteristics (machining yields) in terms of Material Removal Rate (MRR), surface roughness (R_a) of the turned product as well as cutting force F_r (resultant of F_x, F_y and F_z). The work has been conducted in four phases

(Table 3.9). In the first phase, using nonlinear regression analysis, mathematical models have been established to represent functional relationship amongst various process inputs in relation to individual output responses. These mathematical functions have been treated as fitness function evaluation in the ICA based optimization process. The evolutionary optimization technique ICA has been fruitfully explored to obtain the most appropriate parametric combination (process environment) towards optimizing individual characteristics of process performance yield. In later phase of this work, Fuzzy logic has been adapted to convert aforementioned multi-response characteristics into an equivalent single objective function i.e. MPCI (Multi-Performance Characteristic Index). Finally, the fitness function which represents relationship amongst inputs as well as MPCI has been optimized to determine the best setting of process parameters that is capable of simultaneously optimizing multiple performance characteristics to the maximum extent. The result obtained, thereof, has been compared to that of Genetic Algorithm (phase three); good agreement has been observed. This infers application potential of ICA towards optimizing multiple performance characteristics of CFRP composite machining. In last phase of the work, Taguchi based discrete search optimization philosophy has been attempted in order to obtain a feasible optimal setting to validate the results of both ICA as well as GA.

Table 3.9: Chronology of the present work

Phase	1	2	3	4
Objective	Optimization of individual response features	Optimization of MPCI (Multi-Performance Characteristic Index)	Optimization of individual responses as well as MPCI	Optimization of individual responses as well as MPCI
Methodology	Nonlinear regression+ICA	FIS (Fuzzy Inference System)+ Nonlinear regression+ICA	Nonlinear regression+GA (for optimizing individual responses) FIS (Fuzzy Inference System)+ Nonlinear regression+GA (to optimize GA)	Taguchi's optimization philosophy

3.2.3 Experimentation

Experiments have been conducted on Lathe HMT NH26 (manufactured by HMT Machine Tools Kalamasarry, India). From the past literature, it has been observed that the controllable process (turning) parameters namely cutting speed, feed rate and depth of cut impose predominant effect on machining the performance yield. Table 3.10 represents the domain of experiments in which aforementioned parameters have been varied into three different levels. Turning operation has been carried on samples of CFRP (epoxy) composite bars (Fig. 3.15) (ø50x150 mm) (Density: 1.5gm/cm^3, Orientation: 0/60^0, Fibre: Matrix=30:70, Method of Formation: Hand layup) with a single point HSS turning tool. A systematic experimental design layout needs to be followed for proper execution of the experimentation which is capable of reducing experimental cost as well as experimentation time. For this, Taguchi's L_9 Orthogonal Array (OA) has been utilized for selecting the appropriate layout design of experiment (Table 3.11). In order to evaluate machining performance characteristics, Material Removal Rate (MRR), roughness average (R_a) and resultant cutting force (F_r) have been taken under consideration. This is because, MRR is directly related to productivity; whereas, R_a can be interpreted as an important parameter in describing product quality. F_r affects both quality as well as productivity. From the knowledge of past literature, considering their importance in FRP composite machining, aforesaid three responses have been considered in the present case experimental research.

MRR can be defined as the volume of material removed per unit machining time. MRR for each experimental run has been evaluated by using following equation:

$$MRR = \frac{(W_i - W_f)}{\rho . t_m} \frac{mm^3}{min} \tag{3.12}$$

W_i = Initial weight of the work piece, W_f = Final weight of the work piece, ρ = Density of the work material, t_m = Machining time.

In any machining operation, surface quality is one of the major concerns in order to achieve proper assembly of the components. Surface roughness can be considered as the major quality indicator in explaining surface finish as it caused by the repetition action of tool on the work surface, during machining. Surface roughness tester SJ-210 (Make: Mitutoyo) has been used for determining the roughness average (R_a) values. For a particular work piece three values for R_a have been computed at different places of the machined surface, and average of these values has been taken for analysis.

Cutting forces are of vital concern in turning operation as it is responsible for causing dimensional inaccuracy and occurrence of machine tool vibration. It leads to fiber pull out during machining of carbon fiber reinforced composites; and hence, it is required to minimize the cutting forces during operation. Cutting tool dynamometer (Computerized Lathe Tool Dynamometer, Make: MEDILAB ENTERPRISES, Chandigarh, INDIA) has been used for assessment of cutting forces in all three directions (F_X, F_Y and F_Z) while performing turning as shown in Fig. 3.14. The resultant cutting force (F_r) has been computed as below:

$$F_r = \sqrt{F_x^2 + F_y^2 + F_z^2} \tag{3.13}$$

Table 3.12 represents the observed values of the aforementioned machining response characteristics.

In the current experimental research, the following assumptions have been made.

1. Interaction effects of process parameters impose negligible effect on the response(s).
2. Output responses are uncorrelated.

3.2.4 Fuzzy Inference System (FIS)

A Fuzzy Inference System (FIS) defines a nonlinear mapping of the input data vector into a scalar output with the application of fuzzy rules. It has been widely applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision (Jinturkar et al., 2010; Shahriar et al., 2014; Zhang et al., 2003). A fuzzy rule based system consists of four parts:

1. Knowledge base,
2. Fuzzifier,
3. Inference engine and
4. Defuzzifier.

Fuzzifier: The real world input to the fuzzy system is applied to the fuzzifier. In fuzzy literature, this input is called crisp input since it contains precise information about the specific information about the parameter. The fuzzifier convert this precise quantity to the form of imprecise quantity like ‘large’, ‘medium’, ‘high’ etc. with a degree of belongingness to it. Typically the value ranges from 0 to 1.

Knowledge base: The main part of the fuzzy system is the knowledge base in which both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules, whereas, the rule base contains a number of fuzzy IF–THEN rules.

Inference engine: The inference system or the decision making input perform the inference operations on the rules. It handles the way in which the rules are combined.

Defuzzifier: The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to the crisp or in the form of real world input. The main function of defuzzifier is to convert fuzzy input to real world output. Most commonly two types of fuzzy inference systems can be implemented: Mamdani type and Sugeno type. Mamdani's fuzzy inference method is the most commonly viewed fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory and was proposed in 1975 by Ebrahim Mamdani (Mamdani, 1976; 1977). It was used to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani type inference expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. It is possible, and in many cases much more efficient, to use a single spike as the output membership functions rather than a distributed fuzzy set. This type of output is sometimes known as a *singleton* output membership function, and it can be thought of as a pre-defuzzified fuzzy set. It enhances the efficiency of the defuzzification process because it greatly simplifies the computation required by the more general Mamdani method, which finds the centroid of a two-dimensional function. Rather than integrating across the two dimensional function to find the centroid, weighted average of a few data points is used. Sugeno type systems support this type of model. In general, Sugeno type systems can be used to model any inference system in which the output membership functions are either linear or constant. The basic structure of FIS is shown in the following diagram (Fig. 3.15).

3.2.5 Imperialist Competitive Algorithm (ICA)

Imperialist Competitive Algorithm (ICA) is a computational method inspired by the socio-political competition to solve optimization problems of different types (Atashpaz-Gargari and Lucas, 2007; Kaveh and Talatahari, 2010; Aghakhani et al., 2011). Like most of the methods in the area of evolutionary computation, ICA does not need the gradient of the function in its optimization process. From a specific point of view, ICA can be thought of as the social counterpart of genetic algorithms (GAs). ICA is the mathematical model and the computer simulation of human social evolution, while GA is based on the biological evolution of species. Fig. 3.16 shows the flowchart of the Imperialist Competitive Algorithm. This algorithm starts by generating a set of candidate random solutions in the search space of the optimization problem. The generated random points are called the initial *Countries*. Countries in this algorithm are the counterpart of *Chromosome*s in GAs and *Particle*s in Particle Swarm Optimization (PSO) and it is an array of values of a candidate solution of optimization problem. The cost function of the optimization problem determines the power of each country. Based on their power, some of the best initial countries (the countries with the least cost function value), become *Imperialists* and start taking control of other countries (called *colonies*) and form the initial *Empires* (Atashpaz-Gargari and Lucas, 2007). Two main operators of this algorithm are *Assimilation* and *Revolution*. Assimilation makes the colonies of each empire get closer to the imperialist state in the space of socio-political characteristics (optimization search space). Revolution brings about sudden random changes in the position of some of the countries in the search space. During assimilation and revolution a colony might reach a better position and has the chance to take the control of the entire empire and replace the current imperialist state of the empire (Nazari-Shirkouhi et al., 2010). *Imperialistic Competition* is another part of this algorithm. All the empires try to win this game and take possession of colonies of other empires. In each step of the algorithm, based on their power, all the empires have a chance to take control of one or more of the colonies of the weakest empire (Atashpaz-Gargari and Lucas, 2007). Algorithm continues with the mentioned steps (Assimilation, Revolution, Competition) until a stop condition is satisfied.

The basic process involved in ICA algorithm has been discussed as follows:

a) Initialization:

The random solution has been generated in the space for determination of initial location of empires as follows:

$$x_{i,j}^{o} = x_{min} + rand \cdot (x_{i,max} - x_{i,min}) \quad (3.14)$$

Here, $x_{i,j}^{o}$ evaluates the initial value of the ith variable for the jth country; $x_{i,min}$ and $x_{i,max}$ are the minimum and the maximum allowable values for the ith variable; rand is a random number in the interval [0, 1]. If the allowable search space is a discrete one, using a rounding function will also be necessary.

$$country = [p_1, p_2 ...., p_{Nvar}] \quad (3.15)$$

The variable values in the country are represented as floating point numbers. The cost of country is found by evaluating the cost function f at the variables $p_1, p_2 ...., p_{Nvar}$. Then

$$cost = f(country) = f[p_1, p_2 ...., p_{Nvar}] \quad (3.16)$$

The total number of initial countries is set to $N_{country}$ and the number of the most powerful countries to form the empires is equal to N_{imp}. The remaining N_{col} of the initial countries will be the colonies each of which belongs to an empire. All the colonies of initial countries are divided among the imperialists based on their power.

The power of each country, the counterpart of fitness value, is inversely proportional to its cost value. That is, the number of colonies of an empire should be directly proportionate to its power. In order to proportionally divide the colonies among the imperialists, a normalized cost for an imperialist is defined as:

$$C_j = f_{cost}^{(imp,j)} - \max(f_{cost}^{(imp,i)} \tag{3.17}$$

Here, $f_{cost}^{(imp,j)}$ cost is the cost of the jth imperialist and C_j is its normalized cost. The colonies are divided among empires based on their power or normalized cost and for the jth empire it will be as follows:

$$NC_j = Round\left(\left|\frac{C_j}{\sum_{i-1}^{Nimp} C_i}\right|\right) \cdot N_{col} \tag{3.18}$$

Here, NC_j is the initial number of colonies associated to the jth empire which are selected randomly among the colonies. These colonies together with the jth imperialist form the empire number j. Fig. 3.17 represents the initial generation of empires in a given search location.

b) Assimilation:

In the ICA, it refers to movement of colonies towards the imperialistic states in different in directions. Fig. 3.18 represents the movement of colony towards the imperialist by a random value that is uniformly distributed between 0 and $\beta \times d$:

$$\{x\} \approx U(0, \beta \times d) \tag{3.19}$$

where β is a parameter with a value greater than one, and d is the distance between colony and imperialist. $\beta \rangle 1$ makes the colonies to move closer to the imperialist state from both sides.

In order to increase the searching around the imperialist, a random amount of deviation is added to the direction of movement. Fig. 3.19 depicts the new direction which is obtained by deviating the previous location of the country. Here, θ is random number and be given as

$$\theta = U(-\gamma, +\gamma) \tag{3.20}$$

where, γ is a parameter that adjusts the deviation from the original direction. In most of the implementations, a value of about 2 for β and about π/4(Rad) for γ, result in a good convergence of the countries to the global minimum.

c) Imperialist updating:

If the new position of the colony is better than that of its relevant imperialist (considering the cost function), the imperialist and the colony change their positions and the new location with a lower cost becomes the imperialist. Then the other colonies move toward this new position. This mechanism has been shown in Fig. 3.20 and Fig. 3.21.

d) Imperialistic competition:

Imperialistic competition is another policy utilized in the ICA methodology in which all empires try to take the control of colonies of other empires and control them. The imperialistic competition gradually reduces the power of weaker empires and increases the power of more powerful ones. The imperialistic competition is modelled by capturing some of the weakest colonies of the weakest empires and making a competition among all empires to possess these colonies. In this competition based on their total power, each of empires will have a possibility of taking possession of the mentioned colonies.

Total power of an empire is mainly affected by the power of imperialist country. But the power of the colonies of an empire has an effect, though negligible, on the total power of that empire. This fact is modelled by defining the total cost as

$$TC_j = f_{cost}^{(imp,j)} + \xi \cdot \frac{\sum_{i=1}^{NC_j} f_{cost}^{col,i}}{NC_j} \tag{3.21}$$

where TCj is the total cost of the jth empire and n is a positive number which is considered to be less than 1. A small value for n causes the total power of the empire to be determined by just the imperialist and increasing it will add to the role of the colonies in determining the total power of the corresponding empire. The normalized total cost is defined as

$$NTC_j = TC_j - \max(TC_i) \tag{3.22}$$

where NTCj is the normalized total cost of the jth empire. Having the normalized total cost, the possession probability of each empire is evaluated by:

$$P_j = \left| \frac{NTC_j}{\sum_{i=1}^{Nimp} NTC_j} \right| \tag{3.23}$$

e) Implementation:

When an empire loses all of its colonies, it is assumed to be collapsed. In this model implementation, where the powerless empires collapse in the imperialistic competition, the corresponding colonies will be divided among the other empires.

f) Terminating criterion control:

During the searching process, colonies are moving towards imperialists continuously, hence termination criteria come into existence when the maximum generation number is achieved or the amount of improvement in the best result reduces to a pre-defined value.

The above steps can be summarized as the below pseudo code (Nazari-Shirkouhi et al., 2010)

0) Define objective function: $f(X), X = (x_1, x_2, ..., x_d);$

1) Initialization of the algorithm. Generate some random solution in the search space and create initial empires.

2) Assimilation: Colonies move towards imperialist states in different in directions.

3) Revolution: Random changes occur in the characteristics of some countries.

4) Position exchange between a colony and Imperialist. A colony with a better position than the imperialist has the chance to take the control of empire by replacing the existing imperialist.

5) Imperialistic competition: All imperialists compete to take possession of colonies of each other.

6) Eliminate the powerless empires. Weak empires lose their power gradually and they will finally be eliminated.

7) If the stop condition is satisfied, stop, if not go to 2.

8) End

Like for PSO, the first version of ICA was proposed for solving continuous optimization problems. Then in other works different variants of ICA were proposed for solving both discrete and continuous problems. For example Chaotic ICA was proposed by (Duan, et al., 2009) and also a version of this algorithm for handling constrained optimization problems was proposed by (Zhang, et al., 2009). ICA is now being used to solve different optimization problems in various areas of engineering and science. The following are some of the applications of this algorithm (Rajabioun et al., 2008; Atashpaz-Gargari et al., 2008; Khabbazi et al., 2009; Jolai et al., 2010; Shokrollahpour et al., 2011; Forouharfard and

Zandieh, 2010; Karimi et al., 2010; Bagher et al., 2011; Sarayloo and Tavakkoli-Moghaddam, 2010; Yousefi and Mohammadi, 2011).

- Designing controller for industrial systems
- Solving optimization problems in communication systems
- Solving scheduling and production management problems
- Training and analysis of Artificial Neural Networks
- Design and thermodynamic optimization of plate-fin heat exchangers

3.2.6 Data Analysis and Interpretation

The following sections describe entire data analysis (phase wise) followed by results and discussions.

3.2.6.1 Optimization of Individual Performance Features (Phase 1)

Nonlinear regression model is the type of regression analysis which is used to establish the relationship between the dependent variable and a set of independent variables (Kayabasi, 2012; Yasar et al., 2012). In contrast to traditional linear regression, which is constrained to estimating linear models, nonlinear regression can estimate models with arbitrary relationships between independent and dependent variables. This is accomplished using iterative estimation algorithms. The proposed mathematical model for response is represented as below:

$$Y_u = C \times N^a \times f^b \times d^c \tag{3.24}$$

Here C represents the constant; N represents spindle speed; f represents feed rate; d is the depth of cut. a , b , c are estimated coefficients of the said regression model. In the present work, Gauss-Newton algorithm has been used to generate the coefficients by using SYSTAT 7.0 software package.

$$MRR = 30.493 \times N^{0.972} \times f^{0.414} \times d^{(-0.147)} \tag{3.25}$$

$$R_a = 97.381 \times N^{(-0.588)} \times f^{(-0.572)} \times d^{(-0.139)} \tag{3.26}$$

$$F_r = 17.069 \times N^{0.187} \times f^{0.435} \times d^{(-0.033)} \tag{3.27}$$

The adequacy of a mathematical model can be checked by the value of it's coefficient of determination. Coefficient of determination R^2 is statistical measure which reveals how well data are fitted to model or in other words, it can be defined as percentage of the response variation that can be explained by a model. It varies from range 0 (indicates that model does not explain any variation) to 100% (explain all the variation).Generally, higher value of R^2 is preferred for a model. The R^2 values for the MRR model appears as 98.5%, R_a model corresponds to R^2 value 98.1%, whereas, for F_r is comes 99.6%. Therefore, it can be concluded that these models are adequate enough and can reliably be explored as the fitness functions (objective functions) for ICA optimization algorithm.

Single objective function has been performed aiming to maximize the MRR, and to minimize the surface roughness and cutting force, individually. The upper and lower limits specified in Table 3.10 have been used as variable boundary condition for the input parameters: spindle speed, feed rate and depth of cut. The equation obtained by nonlinear regression analysis has been treated as fitness function to ICA which has to be minimized. The initial parameter setting for ICA has been presented in Table 3.13. The convergence curve for each response (MRR, surface roughness and resultant force) has been shown in Fig. 3.22, Fig. 3.23, and Fig. 3.24. The fitness value for each response with their parametric combination has been shown in Table 3.14.

3.2.6.2 Optimization of MPCI (Phase 2)

In first part of data analysis **(Section 3.2.6.1)**, response characteristics (MRR, R_a and F_r) have been optimized individually. Based on the experimental data, mathematical relationship (amongst inputs and output(s)) has been developed for each of the response features (Eq. 3.25-3.27) through nonlinear regression analysis. Each mathematical function (objective function) has been individually optimized by ICA algorithm.

In practice, any process/product performance is characterized by multi-performance features; and, hence, optimization of single response may not be fruitful always; because, the optimal settings may appear to be different for different objective functions. Therefore, a unique optimal process environment is indeed required which can satisfy (optimize) multiple process performance characteristics simultaneously, to the maximum possible extent. In doing so, firstly, multi-performance features needs to be clubbed (aggregated) to obtain an equivalent single objective function. The aforesaid single objective function (MPCI, in the present case) needs to be optimized finally. Fuzzy Inference System (FIS) has been adapted in this work in order to combine (aggregate) multi-performance output characteristics (MRR, R_a and F_r) into an equivalent single performance index called MPCI (Multi-Performance Characteristic Index). In order to avoid diverse units, data variation range as well as conflict in criteria requirements (MRR: Higher-is-Better; R_a: Lower-is-Better; F_r: Lower-is-Better), experimental data (Table 3.12) have been normalized (Table 3.15) first. The normalized response data have been fuzzyfied (in consideration with appropriate membership function: Figs. 3.26-3.28) and fed as inputs to the FIS designed (Fig. 3.25). The FIS has been designed in such a way that it could provide only fuzzy-single output (MPCI), based on the membership functions designated to define MPCI (Fig. 3.29) as well as rule matrix provided (Table 3.16; Fig. 3.30). The fuzzy MPCI values have been defuzzyfied again and considered as crisp data for single objective function i.e. MPCI (Table 3.15). The MPCI data (from Table 3.15) has been explored to develop a mathematical model (Eq. 3.32) using nonlinear regression analysis. This mathematical model exhibits functional relationship amongst process parameters (spindle speed, feed and depth of cut) in relation with MPCI. Finally, this model has been optimized (maximized) using ICA algorithm. Aforesaid optimization module has been described in detail below.

In order to determine the solution for the multi-response optimization; combined objective function need to be developed. For this, fuzzy logic has been implemented to convert multi-objective responses (i.e. MRR, surface roughness and cutting force) into single an equivalent objective. Initially, all the output responses i.e. MRR, surface roughness and cutting force should be normalized so that all values come within the range 0 to 1 (where 0 is considered as worst value and 1 is best value). The normalized data has been presented in Table 3.35. For the normalization purpose, following equations have been used:

For the Lower- is-Better (LB) criterion:

$$y_{ij} = \frac{x_{ij} - \max x_{ij}}{\min x_{ij} - \max x_{ij}} \tag{3.28}$$

For the Higher- is-Better (HB) criterion:

$$\mathrm{y_{ij}} = \frac{\mathrm{x_{ij}} - \min \mathrm{x_{ij}}}{\max \mathrm{x_{ij}} - \min \mathrm{x_{ij}}} \tag{3.29}$$

Here, $\mathrm{x_{ij}}$ is experimental value whereas, $\max \mathrm{x_{ij}}$ is the maximum value $\min \mathrm{x_{ij}}$ is minimum observed value.

In fuzzy inference system (Fig. 3.25); individual normalized values of each responses (for MRR, roughness average and cutting forces) has been treated as input variables. Aforementioned input variables have been expressed into linguistic terminology using three fuzzy membership functions viz. “Low (L)”, “Medium (M)”, and “High (H)”; whereas, output response (MPCI) has been expressed using five membership functions viz. “Very Low (VL)”, “Low (L)”, “Medium (M)”, “High (H)”, and “Very High (VH)” (Figs. 3.26-3.29).

In this work, the fuzzy set comprises for each input variable and output variable as a symmetric Gaussian membership function. On the basis of fuzzy rules (Table 3.16; Fig.

3.30), the Mamdani implication method has been employed for fuzzy inference reasoning. To obtain a rule,

$R_i : \text{if} x_1 \text{is} A_{i1}, x_2 \text{is} A_{i2}, \text{and} x_s \text{is}$

Then y_i is c_i, $i = 1,2,.........., M$

The linguistic terms in Gaussian membership function has been given as the following

$$\mu_{A^i}(x) = \exp\left(-\frac{(c_i - x)^2}{2\sigma^2}\right) \quad (3.30)$$

Here c_i and σ_i are the centre and width of the i^{th} fuzzy set A^i, respectively.

The output $u_{agg}(y)$ of Mamdani- type fuzzy inference system has to be expressed by a crisp value for the next operation of the fuzzy controller. Centre of gravity (COG) method has been adapted for the defuzzification. The MPCI value obtained has been tabulated in Table 3.15.

$$Y_0 = \frac{\sum_{i=1}^{m} y_i u_{agg}(y_i)}{\sum_{i}^{m} u_{agg}(y_i)} \quad (3.31)$$

ICA has been implemented on the fitness function which has been derived by using non regression analysis on MPCI. R^2 for this model appears as 97.1% which indicates that the model is adequate enough.

$$MPCI = 0.499 \times N^{0.210} \times f^{0.512} \times d^{(-0.186)} \quad (3.32)$$

Fig. 3.31 shows the convergence history for the result of the ICA method. The global optimal value is 0.644989318507148 with optimal combination in Table 3.17.

A comparative study has been made between the optimal setting as obtained by ICA and the same as obtained by Taguchi's optimization philosophy. The optimal setting for maximizing MPCI (in case of ICA) appears (N=1020 RPM, f=0.08 mm/rev, and d=0.6 mm); whereas, an optimal setting (N=1020 RPM, f=0.08 mm/rev, and d=0.8 mm) has been obtained by maximizing MPCI using Taguchi method (Table 3.18; Fig. 3.32). The fitness function value (predicted MPCI) for ICA appears as 0.644989318507148; whereas, Taguchi's predicted MPCI value becomes 0.710440972 at the predicted optimal level. Another check has been made i.e. ICA predicted optimal setting has been fed to the Taguchi module to predict the MPCI value which appears 0.709497 which is nearly equal to 0.710440972. The compatibility of aforesaid results ensures application feasibility of ICA optimization algorithm. For N and f, predicted optimal values for both the case (ICA and Taguchi method) appear same; difference is only in d value. Slight change in d value did not affect the fitness function value in an amplified manner.

Confirmatory test has been conducted finally to validate the predicted optimal setting. The predicted optimal setting as obtained by maximizing MPCI through ICA algorithm appears to be: N= 1020 RPM; f=0.08 mm/rev and d=0.6 mm. Experimental test has been conducted using that particular optimal parameters setting; and the corresponding response values observed are: MRR=9627.83 mm3/min, R_a=6.79333 µm and F_r= 15.138 Kgf; which appears satisfactory as compared to (Table 3.12) in view of individual criteria requirements of individual responses (MRR: Higher-the-Better; R_a: Lower-the-Better and F_r: Lower-the-Better).

3.2.6.3 Results and Discussions: Comparison between ICA and GA (Phase 3)

The effectiveness of the proposed algorithm (ICA) has been compared with the performance of Genetic Algorithm (GA) in view of the obtained optimal machining condition. The initial tuning parameters for each algorithm i.e. GA and ICA have been listed in Table 3.19. It is clear from Table 3.19 that ICA works under less number of tuning parameters as compared to GA which certainly reduces the computational error as well as complexity.

The fitness value for MRR, roughness average (R_a), resultant cutting force (F_r) and finally MPCI appears as 9706.22918041811, 6.85241509677932, 16.5194921686056, and 0.6449893, respectively, through exploration of ICA; whereas, the fitness value for MRR, roughness average (R_a), resultant cutting force (F_r) and finally MPCI obtained as 9695.978392, 6.85972, 16.62534, and 0.6433, respectively by employing GA (Table 3.20). Convergence curve of each of the aforesaid responses obtained through GA have been depicted in Figs. 3.33-3.36. The fitness value obtained by ICA for each response has been found higher (and that has been obtained in a lesser number of iterations) as compared to GA, which is highly desirable (Table 3.20). Hence, results illustrated above infer that ICA appears to be compatible (relatively better) in view of its performance as compared to GA.

3.2.6.4 Results of Taguchi's Optimization Philosophy (Phase 4)

The main difference between evolutionary based optimization approach and Taguchi philosophy is that: most of the algorithms search the global optima within a continuous search domain. On the contrary, Taguchi's optimization philosophy is based on discrete search. It searches the optimal setting of process parameters within some discrete level values in experimental domain which can easily be adjusted in the machine/ setup. Because, in most of the machines; provision is there to vary controllable process parameters within few discrete levels. Parameters cannot assume any value which means experimental domain is not continuous. Therefore, the optimal setting obtained through Taguchi approach may not provide global optima. In contrast to that, applications of optimization algorithms (based on continuous search) are capable of predicting the global optima. However, the global optima thus predicted cannot be set in the machine/setup where discrete parametric values are possible to set. Therefore, the optimal values of process parameters need to be altered (slightly higher or lower value available in the machine) before fixing up in the machine for practical application. Considering optimal setting of individual response features, it has been observed that for MRR; optimal setting as predicted by GA is [N=1019.47543 RPM, f=0.07997 mm/rev, d=0.60169 mm] obtained through GA which can be approximated to [N=1020 RPM, f=0.08 mm/rev, d=0.6 mm] which is the outcome of ICA as well as Taguchi method (Tables 3.21-3.22, Fig. 3.37). Similarly, it has been observed that for R_a; optimal setting as predicted by GA is [N= 1018.19264 RPM, f=0.07999 mm/rev, d=1.1999 mm] obtained through GA which can be approximated to [N=1020 RPM, f=0.08 mm/rev, d=1.2 mm] which is the outcome of ICA as well as Taguchi method (Tables 3.21-3.22, Fig. 3.38). For, F_r, optimal setting as predicted by GA is [N=605 RPM, f=0.06 mm/rev, d=0.943 mm] obtained through GA; and the setting [N=605 RPM, f=0.06 mm/rev, d=0.9 mm] obtained through ICA. The optimal setting for F_r appears as [N=605 RPM, f=0.07 mm/rev, d=0.9 mm] in Taguchi method (Tables 3.21-3.22, Fig. 3.39). Comparing optimal settings for F_r obtained through GA, ICA and Taguchi method; it has been found that the optimal settings appear same for GA as well as ICA. Taguchi predicted optimal setting appears slightly different i.e. in feed (f=0.7 mm/rev) which has been obtained as (f=0.6 mm/rev) in GA and ICA. From Table 3.10, it has been observed that 0.6 mm/rev and 0.7 mm/rev both can be adjusted in the machine. Moreover, Taguchi predicted S/N Ratio values for F_r at [N=605 RPM, f=0.07 mm/rev, d=0.9 mm] and [N=605 RPM, f=0.06 mm/rev, d=0.9 mm] appear as -24.3584 dB (corresponding fitness value 16.5165) and -24.4195 dB (corresponding fitness value 16.6331), respectively. It infers that both the settings can be used as the optimal parametric combination for minimizing F_r. Slight difference in feed value would not alter the fitness function value.

The comparison of optimal settings (for maximizing MPCI) obtained through ICA, GA and Taguchi method has already been described in **Section 3.2.6.2**.

3.2.7 Concluding Remarks

This work presents an integrated optimization route based on nonlinear regression, fuzzy logic and Imperialist Competitive Algorithm (ICA) in order to evaluate the optimal machining condition in turning of CFRP (epoxy) composites. Nonlinear mathematical model for each performance characteristics has been developed and optimized individually using ICA.

Fuzzy logic has been adopted to convert multi-responses into an equivalent single objective function (MPCI). ICA has been implemented further to evaluate the best fitness value for the MPCI. The basic idea behind this algorithm is the competition among the imperialist for possession of colonies to increase their influence and empires. It has been observed that this algorithm provides reliable results with less computational efforts and time. The performance (efficiency) of ICA has also been compared with respect to (i) Taguchi based optimization philosophy as well as (ii) genetic algorithm; and satisfactory results have been observed. This infers application potential of the proposed optimization route could be explored for offline quality control of any process/product.

The limitations of the aforesaid work have been pointed out below.

The work considered Material Removal Rate (MRR), Roughness Average (R_a) and Resultant Cutting Force (F_r) as important output responses. There are other process responses like (tool-life, extent of tool wear, extent of machine tool vibration, and other roughness parameters (other than R_a) which can also be included in the list of process performance yields during future investigations.

In this work the aspects of material response has not been studied. Material response is basically the response against interference of an external agency. For example, material response of composite material may be tribological behavior (wear response), response due to external load (vibration, fatigue etc.) which are completely different than the response of machining operations performed on those composites. Compared to the external environment (agency) for determining material response; machining environment is completely different. Therefore, material investigation on response appears to be a completely different direction of research.

Fig. 3.13: Samples of machined CFRP (epoxy) composite bars

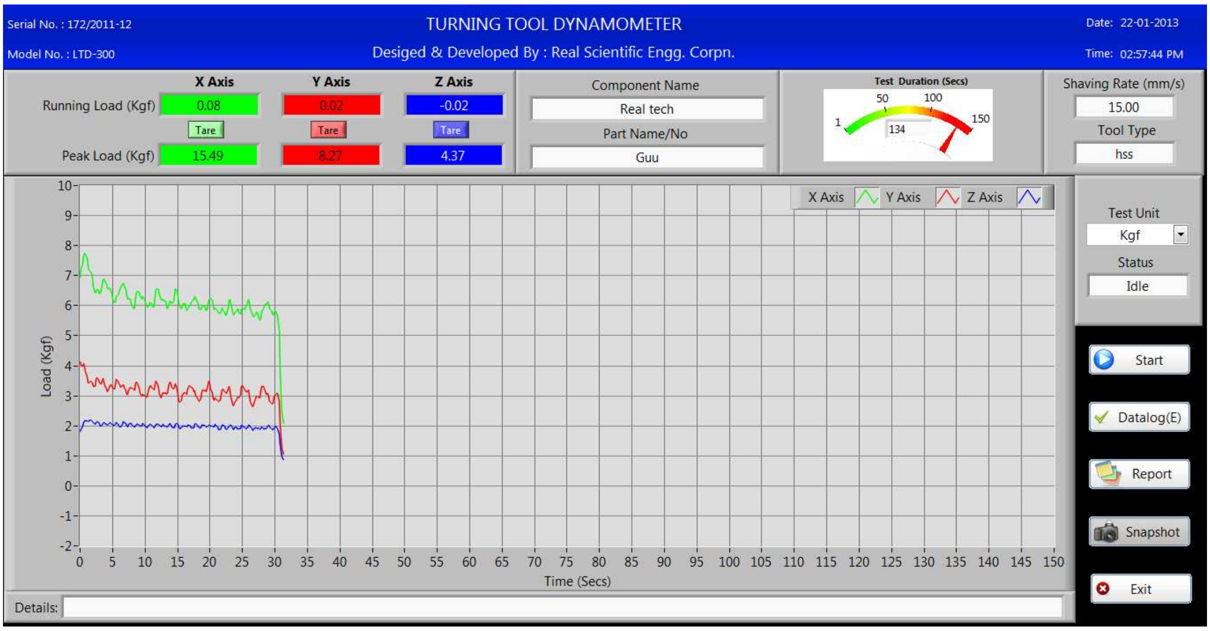


Fig. 3.14: Cutting force evaluation during turning operation

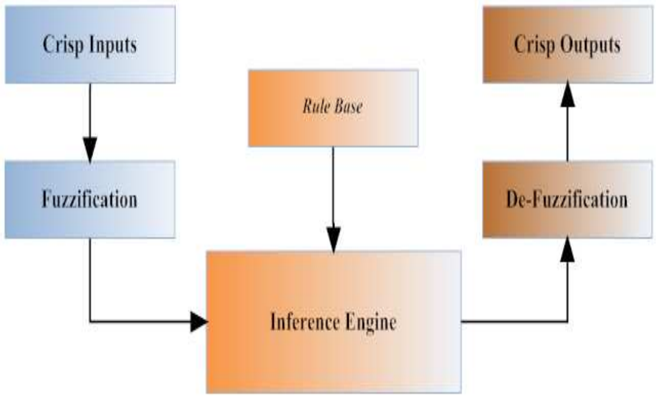


Fig. 3.15: Basic structure of FIS

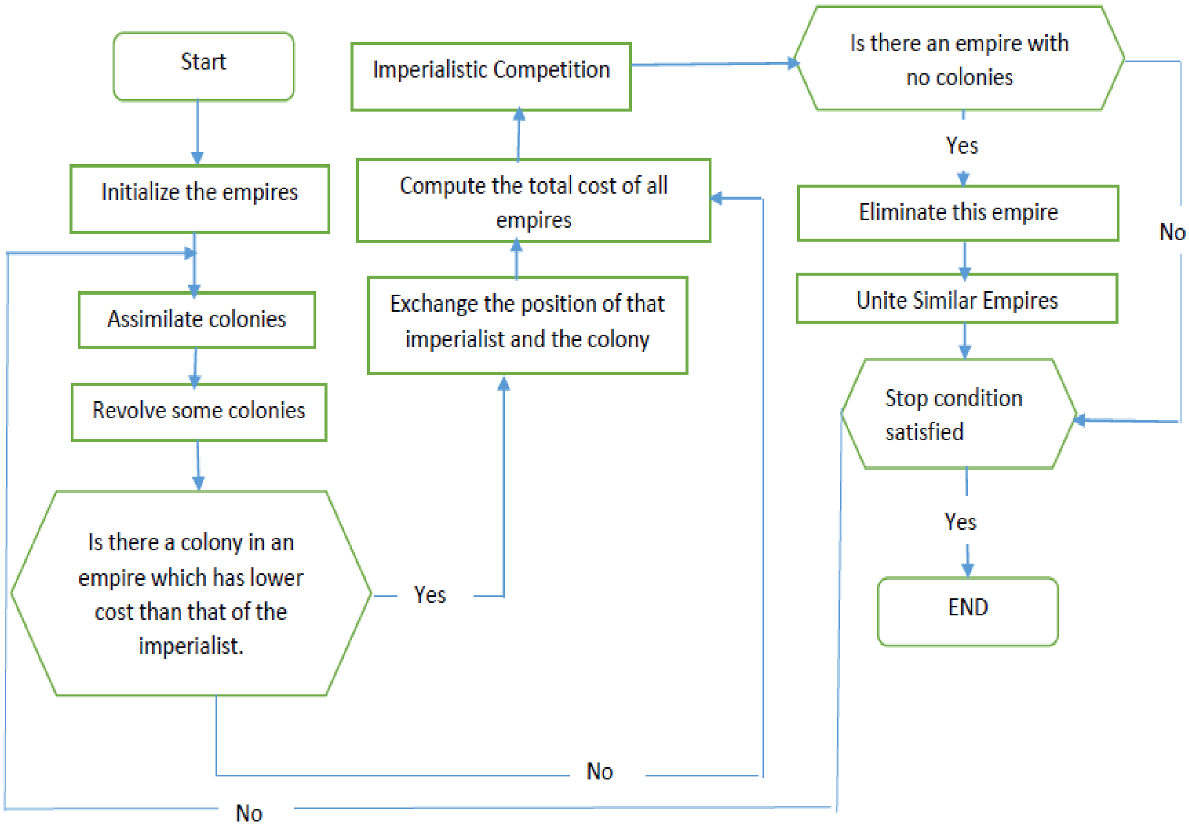


Fig. 3.16: Basic flow chart of ICA algorithm

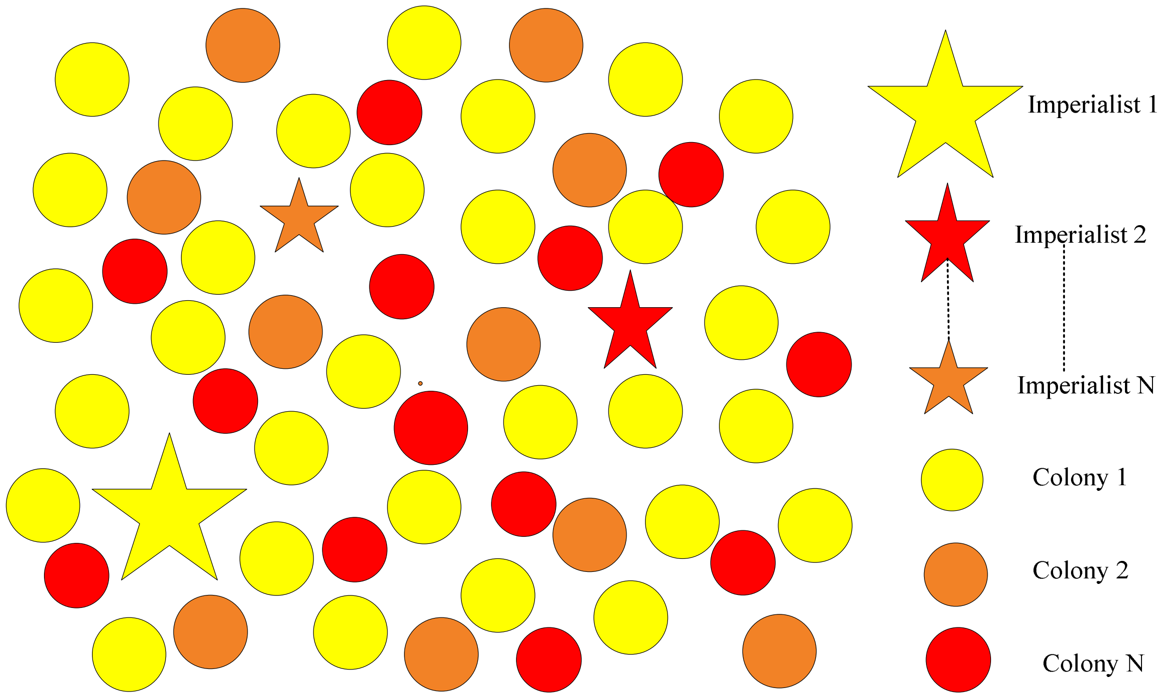


Fig. 3.17: Generation of the initial empires

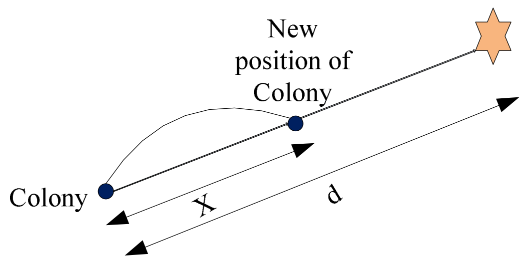


Fig. 3.18: Moving colonies to their significant imperialists

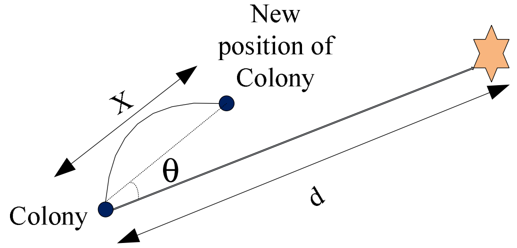


Fig. 3.19: Moving colonies to their significant imperialists in a randomly deviated direction

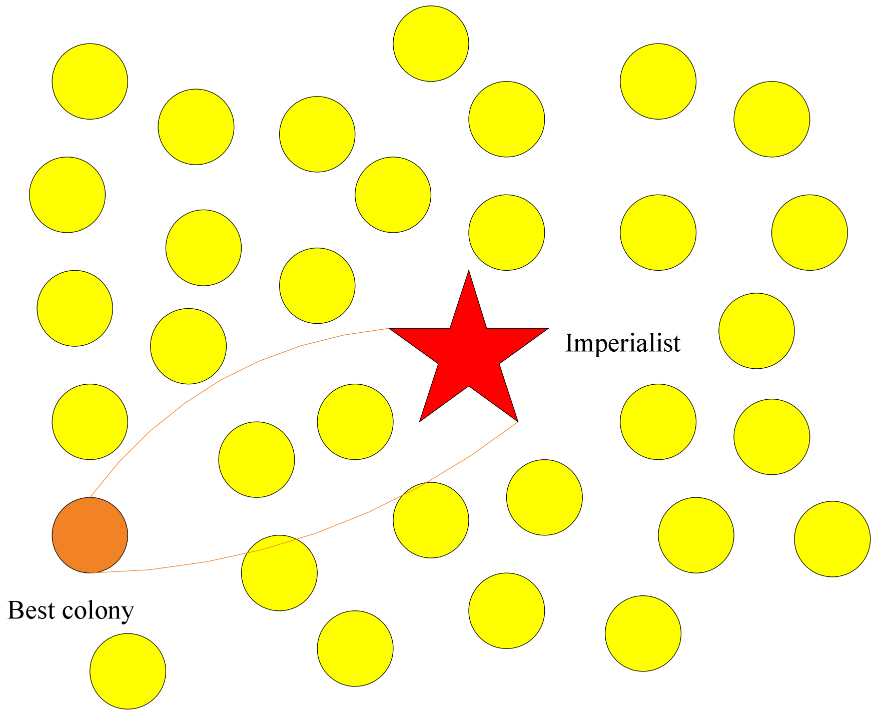


Fig. 3.20: Exchanging the position of colony and Imperialist

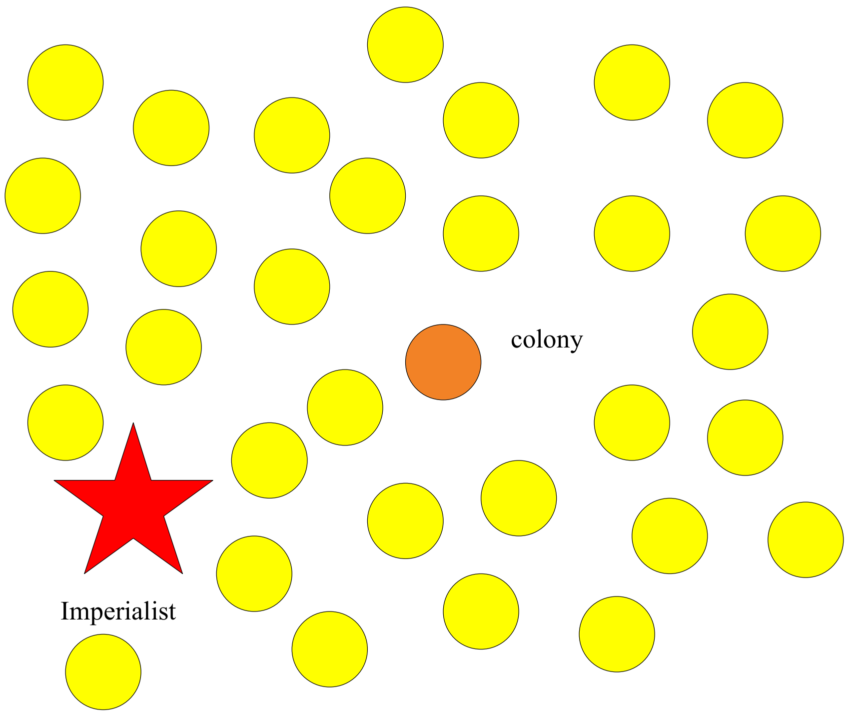


Fig. 3.21: Position of colony and Imperialist after exchanging

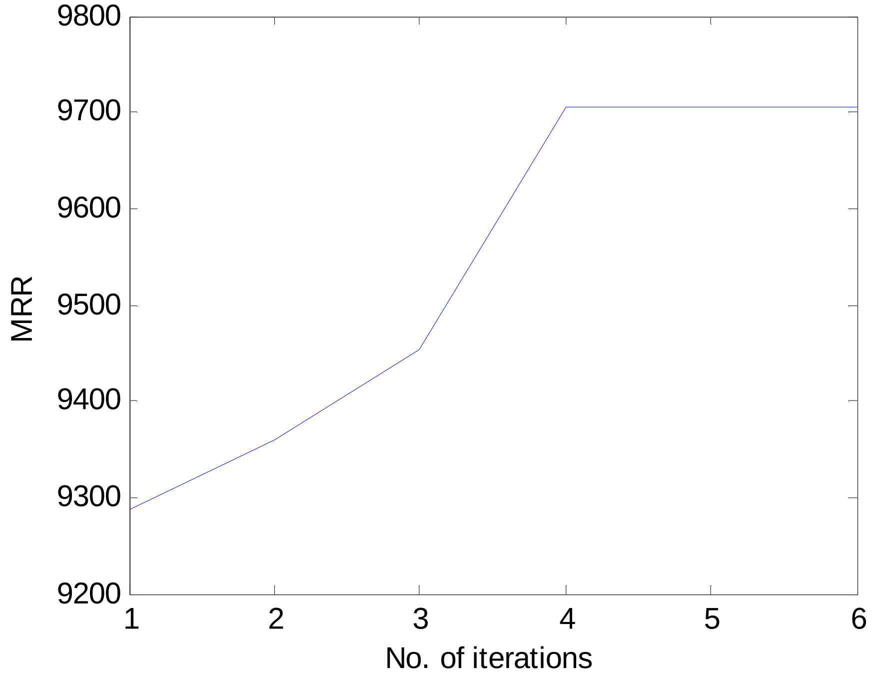


Fig. 3.22: Convergence curve for MRR

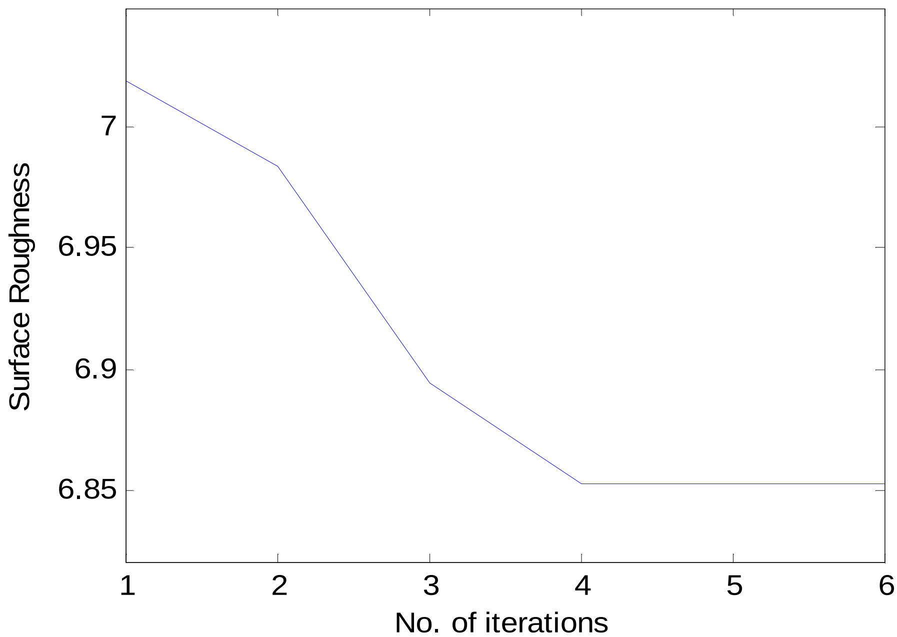


Fig. 3.23: Convergence curve for surface roughness

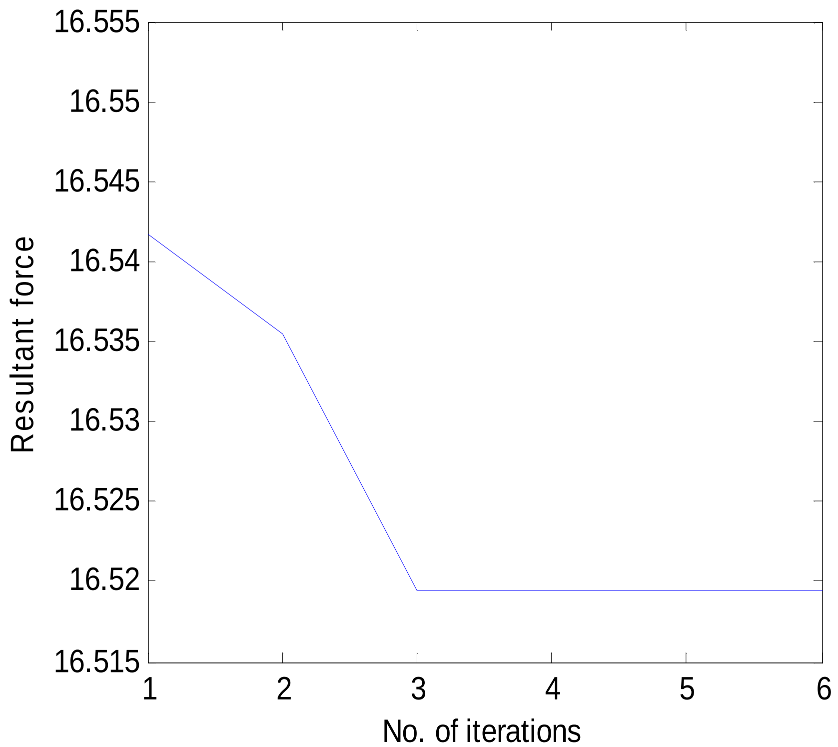


Fig. 3.24: Convergence curve for resultant force

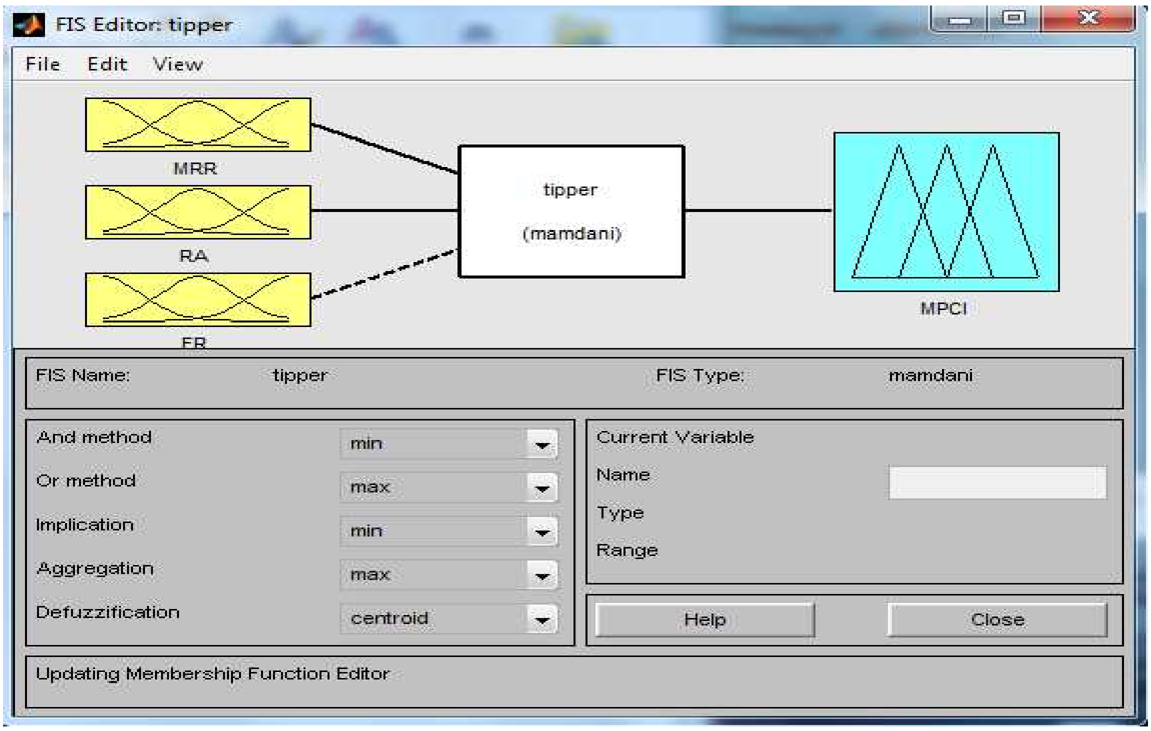


Fig. 3.25: Fuzzy Inference System

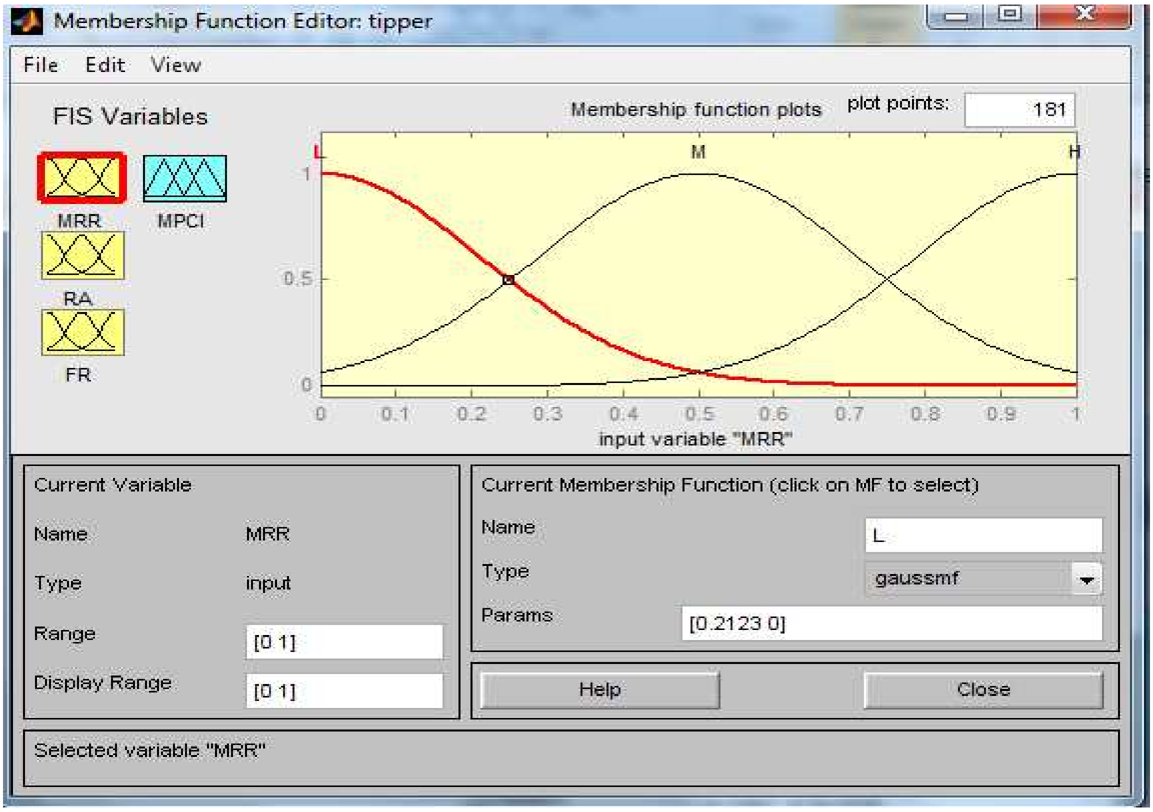


Fig. 3.26: Membership function for MRR

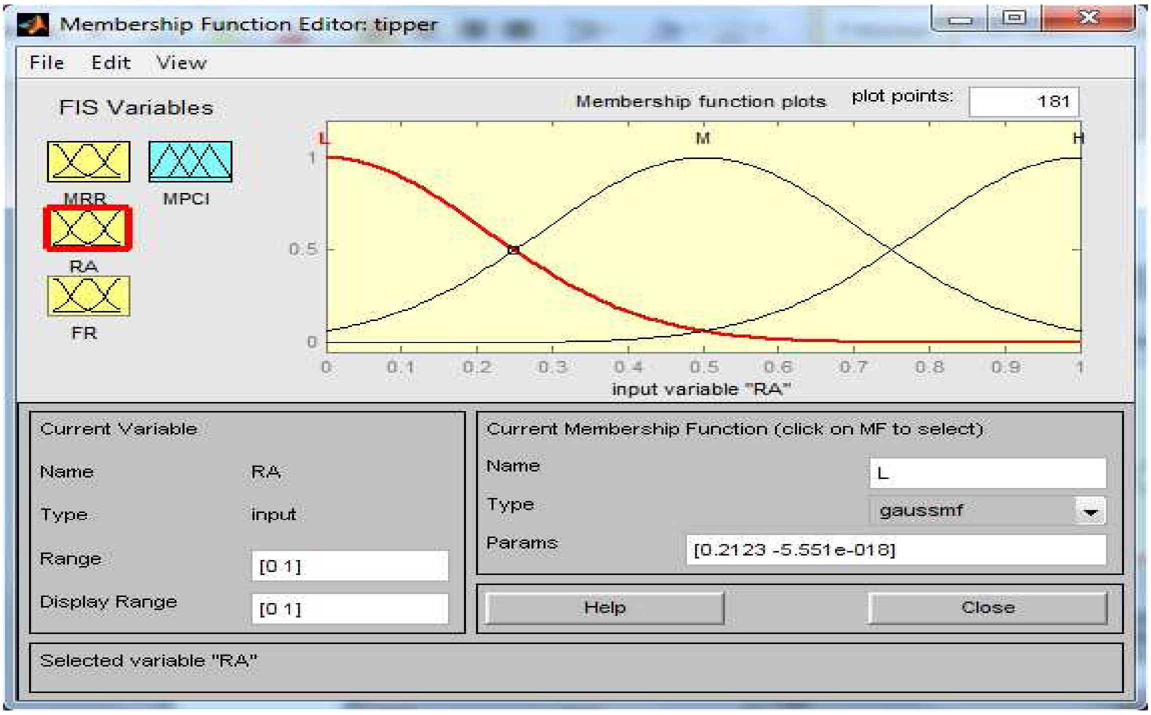


Fig. 3.27: Membership function for Surface roughness

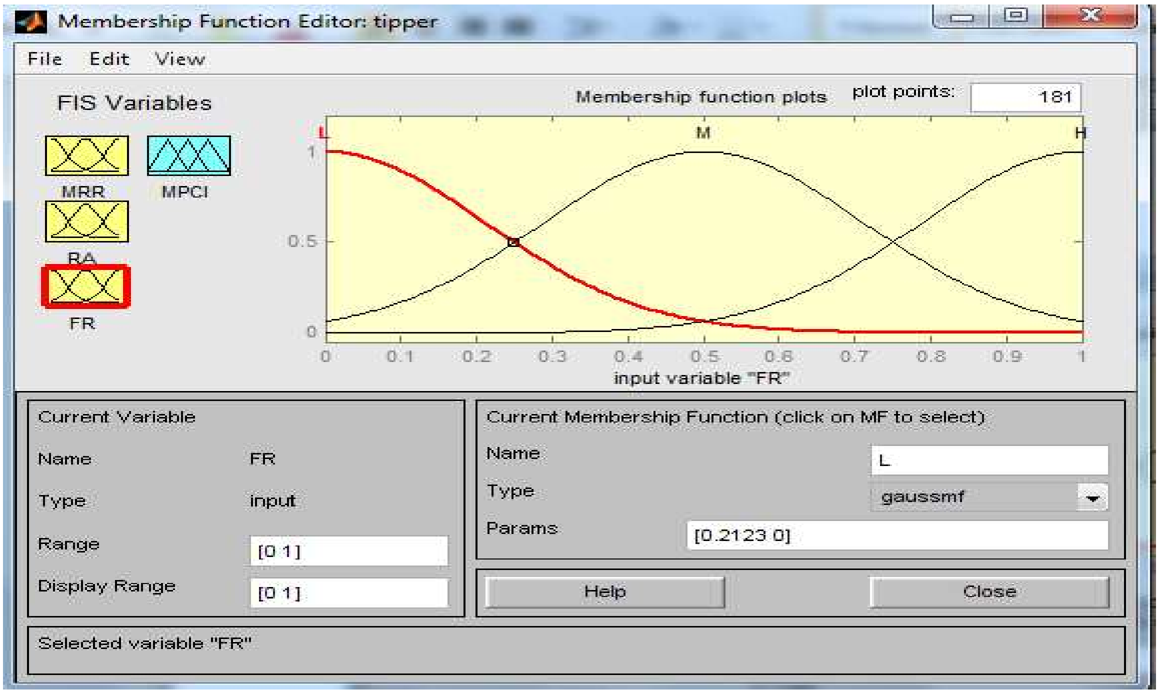


Fig. 3.28: Membership function for resultant force

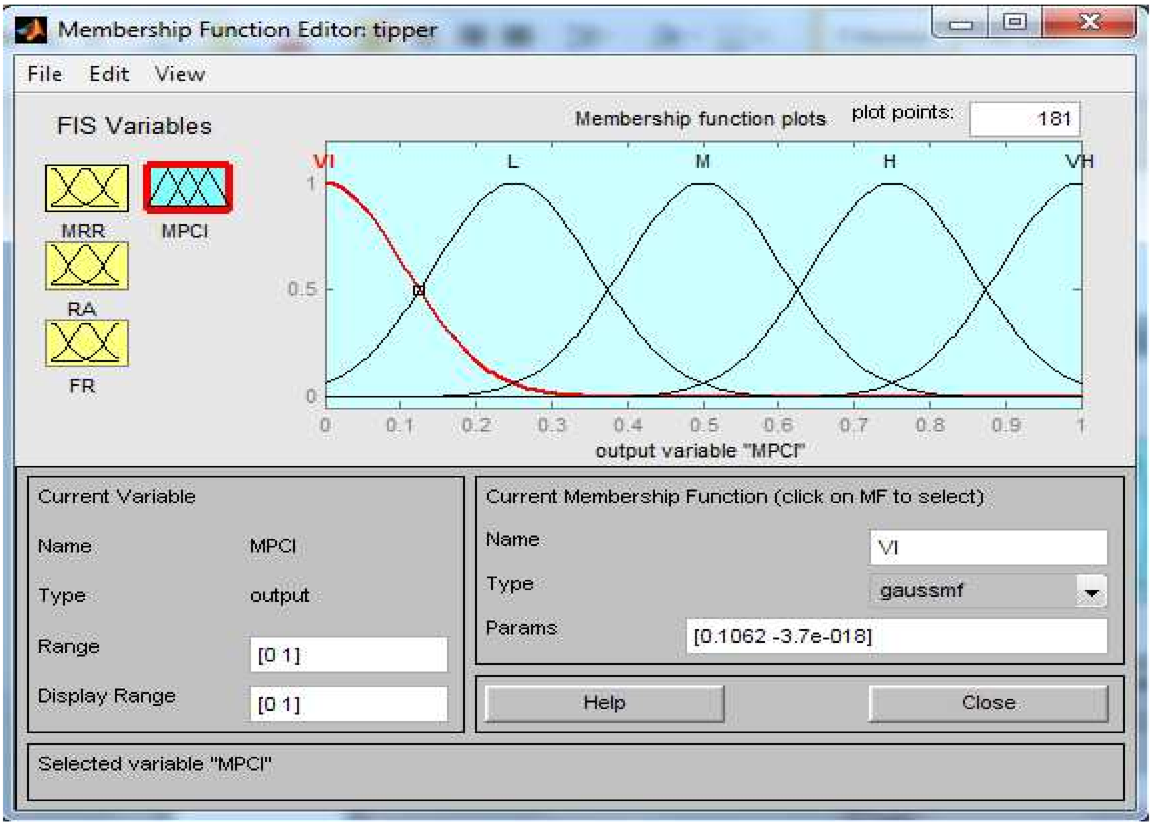


Fig. 3.29: Membership function for MPCI

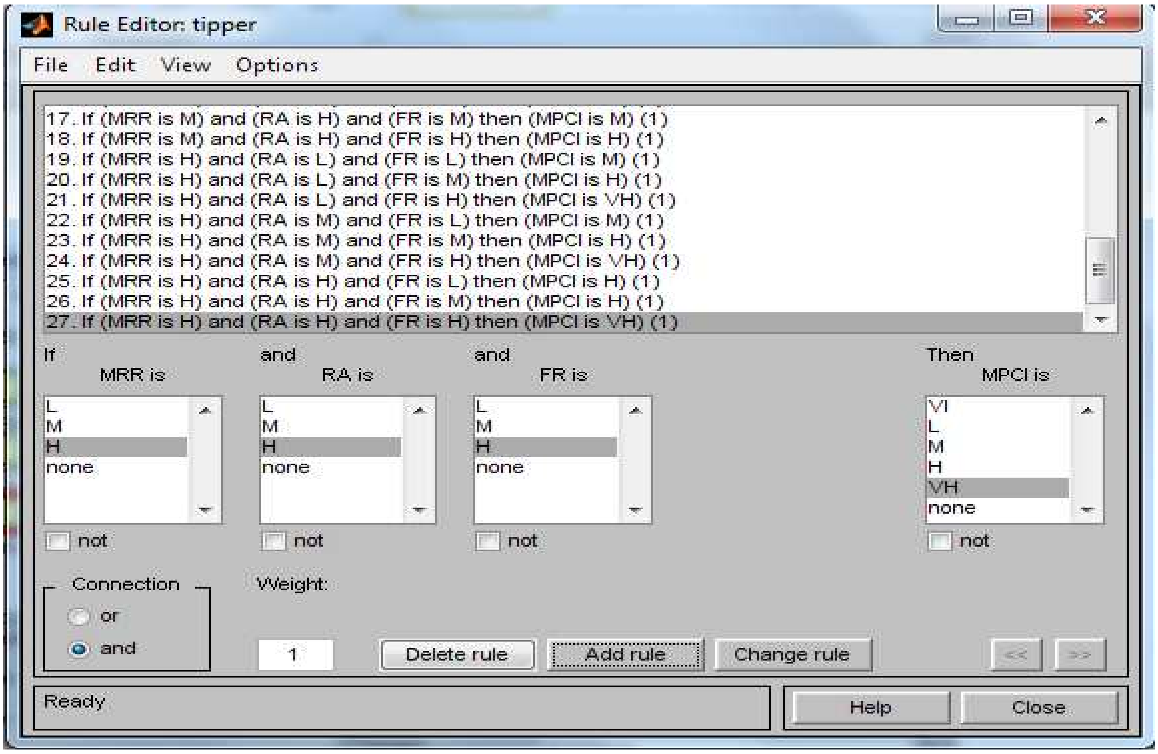


Fig. 3.30: Fuzzy rule editor

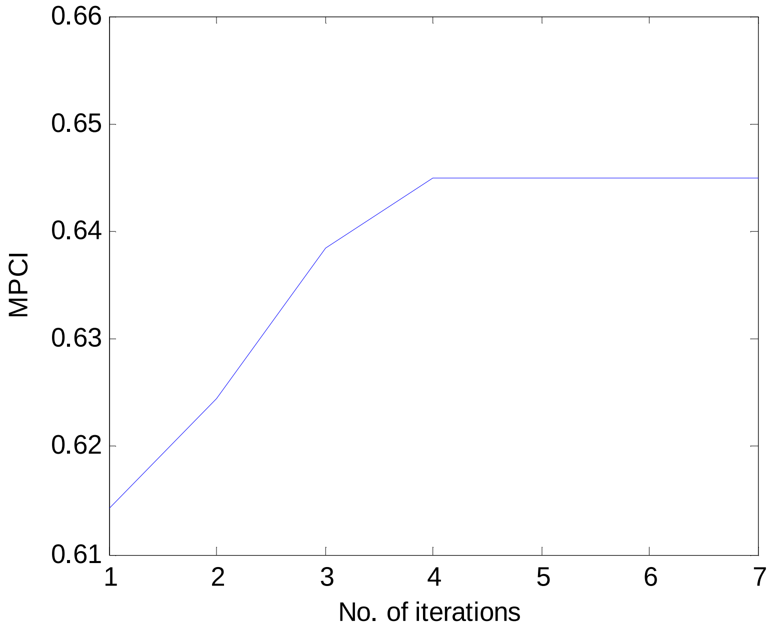


Fig. 3.31: Convergence curve for MPCI

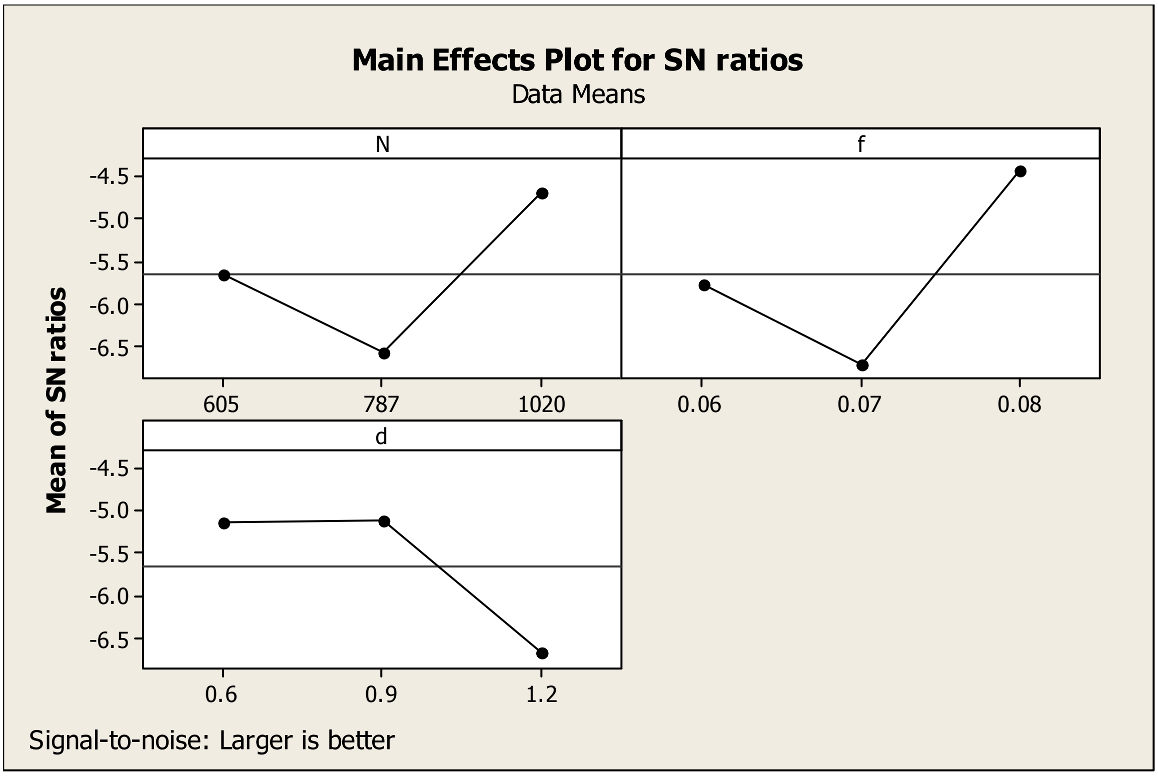


Fig. 3.32: S/N ratio plot for MPCI

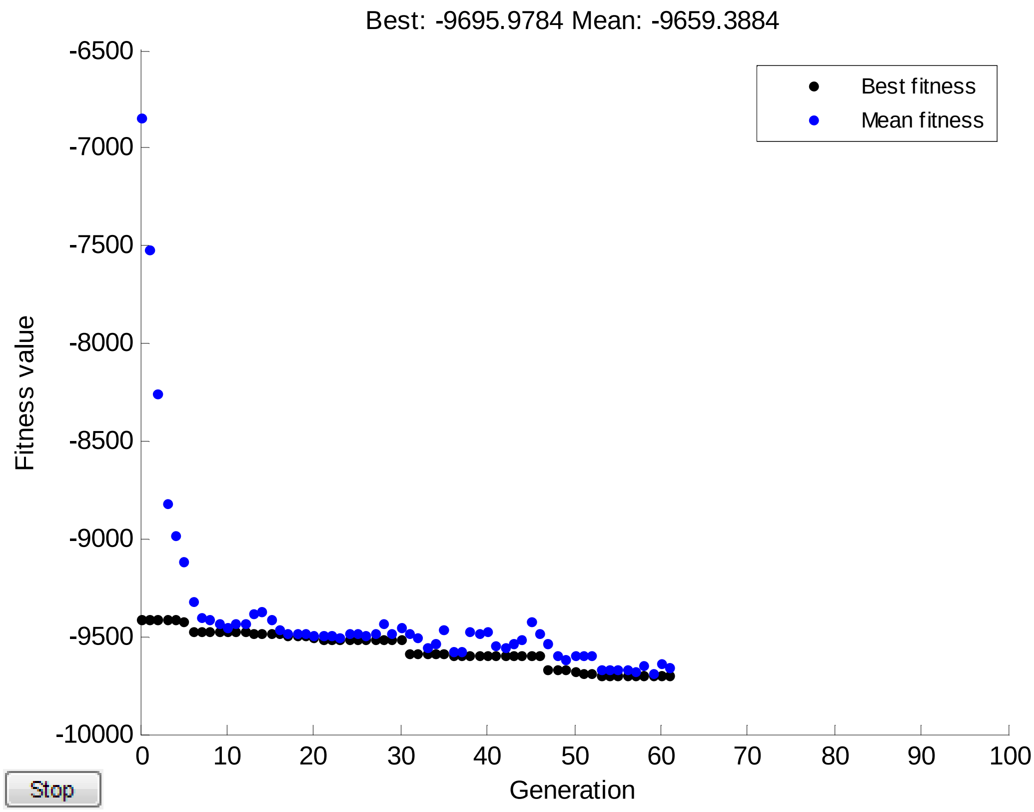


Fig. 3.33: Convergence curve for MRR by using GA

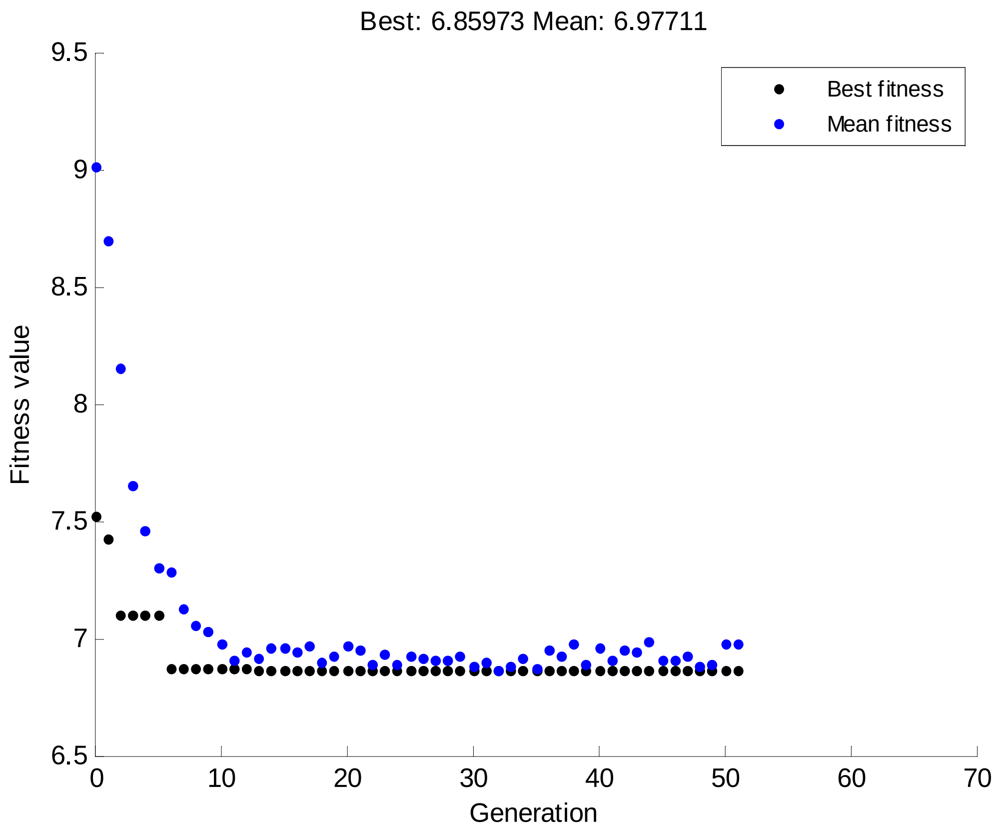


Fig. 3.34: Convergence curve for surface roughness by using GA

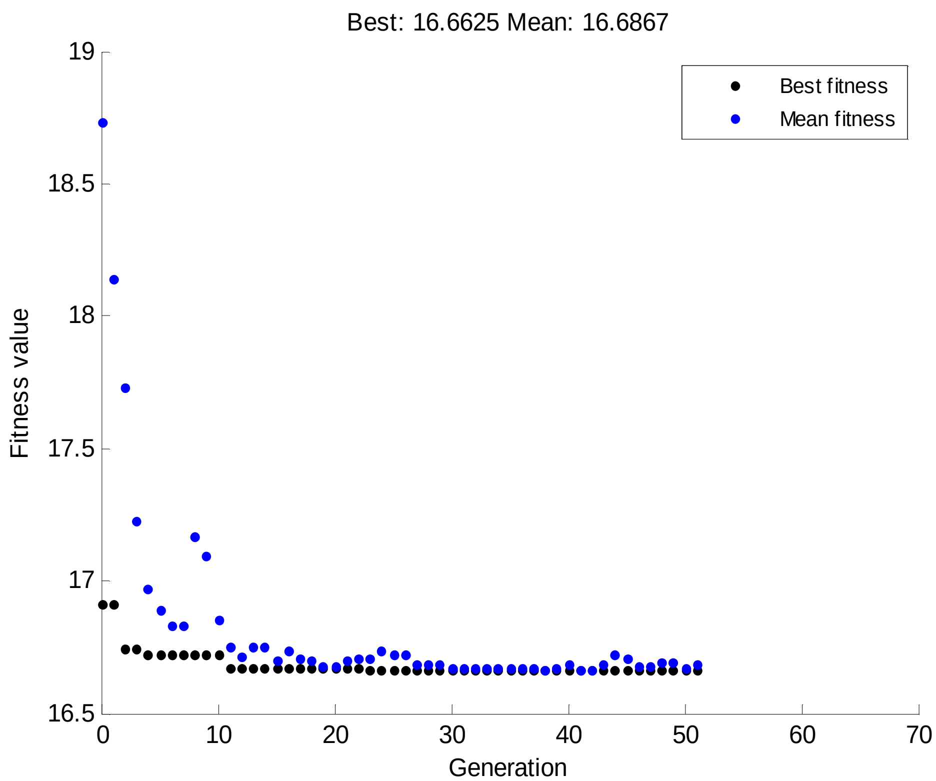


Fig. 3.35: Convergence curve for resultant cutting force by using GA

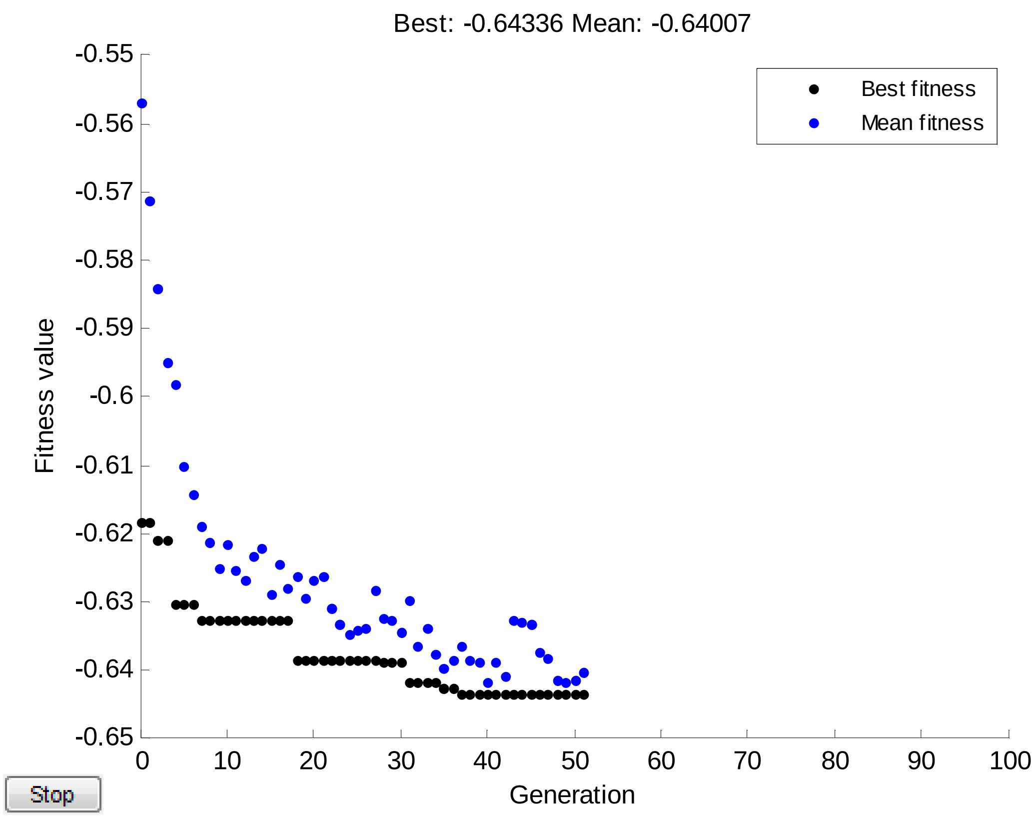


Fig. 3.36: Convergence curve for MPCI by using GA

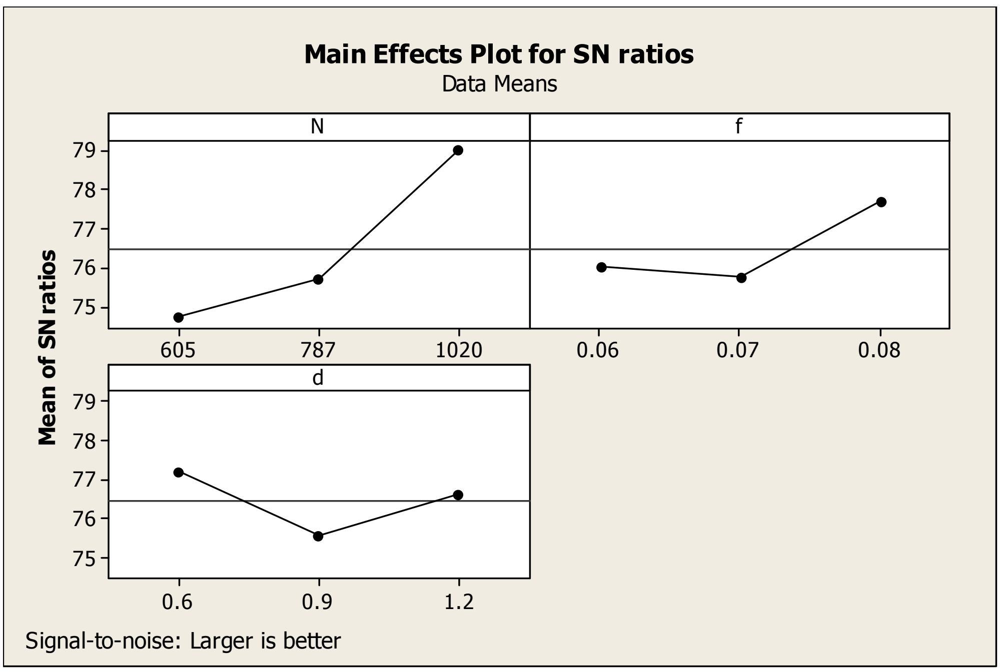


Fig. 3.37: S/N ratio plot for MRR

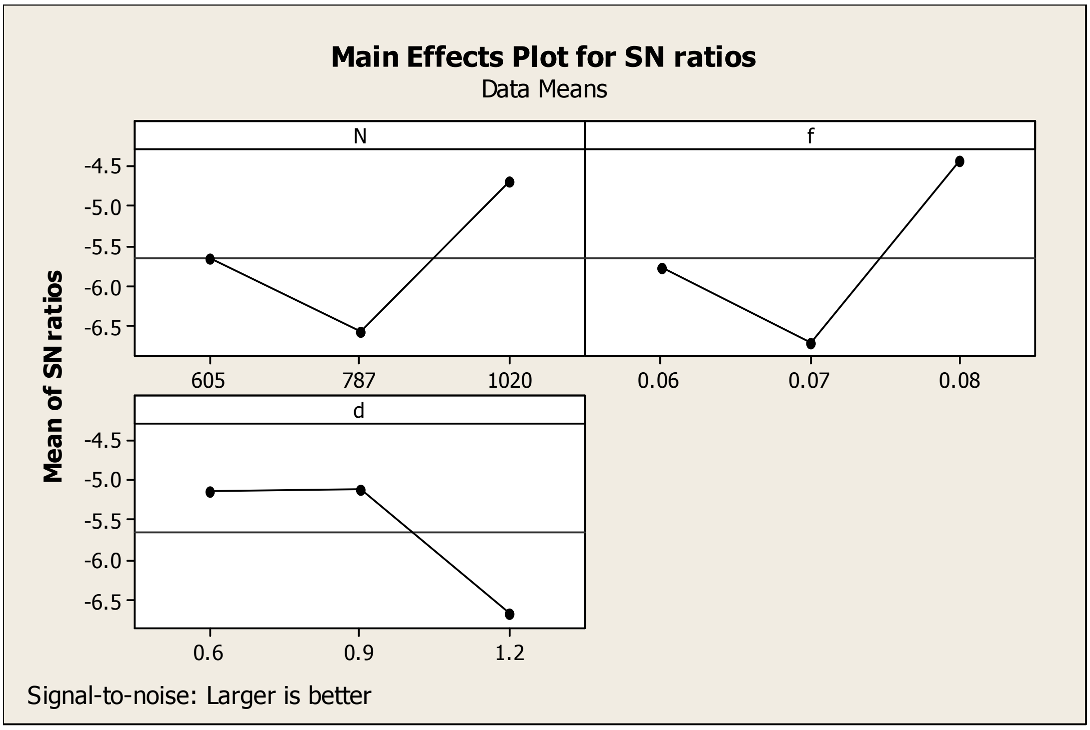


Fig. 3.38: S/N Ratio plot for R_a

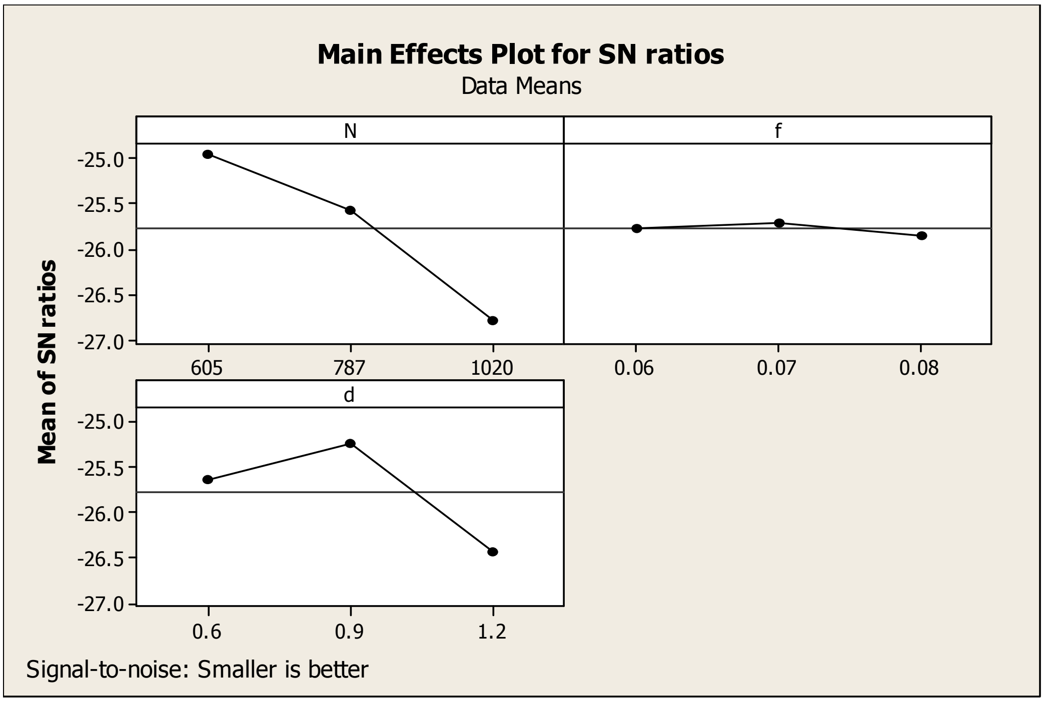


Fig. 3.39: S/N ratio plot for F_r

Table 3.10: Domain of experiments

Factor(s)	Unit	Level 1	Level 2	Level 3
Spindle Speed (N)	[RPM]	605	787	1020
Feed Rate (f)	[mm/rev]	0.06	0.07	0.08
Depth of Cut (d)	[mm]	0.6	0.9	1.2

Table 3.11: Design of experiment (L_9 Orthogonal Array)

Sl. No.	N [RPM]	f [mm/rev]	d [mm]
1	605	0.06	0.6
2	605	0.07	0.9
3	605	0.08	1.2
4	787	0.06	0.9
5	787	0.07	1.2
6	787	0.08	0.6
7	1020	0.06	1.2
8	1020	0.07	0.6
9	1020	0.08	0.9

Table 3.12: Experimental data

Sl. No.	MRR [mm^3/min]	R_a [µm]	F_r [Kgf]
1	5092.315	11.69167	18.095
2	4639.072	13.02433	16.975
3	6851.963	7.299	18.023
4	5612.611	8.223667	16.748
5	5172.299	9.520667	21.154
6	7836.729	9.169667	19.422
7	8797.64	8.815333	24.2235
8	9597.48	7.926333	20.016
9	8372.299	6.946667	21.556

Table 3.13: Parameter settings for ICA

Parameters	Value assigned
Maximum decades	1000
Number of Countries	80
Number of Imperialists	8
Number of Colonies	(No Countries - No Imperialists)
β	2
γ	0.1

Table 3.14: Fitness value for each response

	MRR	R_a	F_r
Optimal combination	N=1020; F=0.08; D=0.6	N=1020; F=0.08; D=1.20	N=605; F=0.06; D=0.9
Fitness value	9706.22918041811	6.85241509677932	16.5194921686056

Table 3.15: Normalized value of experimental results and MPCI

Sl. No.	MRR	R_a	F_r	**MPCI**
1	0.091408976	0.219271783	0.819811384	**0.461**
2	0	0	0.969634138	**0.493**
3	0.446290624	0.942028211	0.829442847	**0.623**
4	0.196341043	0.789886343	1	**0.574**
5	0.10753996	0.576481947	0.410607986	**0.312**
6	0.644895922	0.634234409	0.642298174	**0.576**
7	0.83869016	0.692535437	0	**0.513**
8	1	0.838808766	0.562838606	**0.639**
9	0.752908393	1	0.356832319	**0.602**

Table 3.16: Fuzzy rule matrix

Rule No.	MRR (IF)	R_a (IF)	F_r (IF)	THEN (MPCI)
1	Small	Small	Small	Very small
2	Small	Small	Medium	Small
3	Small	Small	Large	Medium
4	Small	Medium	Small	Very small
5	Small	Medium	Medium	Small
6	Small	Medium	Large	Medium
7	Small	Large	Small	Small
8	Small	Large	Medium	Small
9	Small	Large	Large	Medium
10	Medium	Small	Small	Small
11	Medium	Small	Medium	Medium
12	Medium	Small	Large	Large
13	Medium	Medium	Small	Small
14	Medium	Medium	Medium	Medium
15	Medium	Medium	Large	Large
16	Medium	Large	Small	Medium
17	Medium	Large	Medium	Medium
18	Medium	Large	Large	Large
19	Large	Small	Small	Medium
20	Large	Small	Medium	Large
21	Large	Small	Large	Very large
22	Large	Medium	Small	Medium
23	Large	Medium	Medium	Large
24	Large	Medium	Large	Very large

25	Large	Large	Small	Large
26	Large	Large	Medium	Large
27	Large	Large	Large	Very large

Table 3.17: Fitness Value for MPCI

	MPCI
Optimal combination	N=1020 RPM f=0.08 mm/rev d=0.6 mm
Fitness value	0.644989318507148

Table 3.18: S/N ratio table for optimizing MPCI using Taguchi method

Design of Experiment			MPCI	S/N Ratio of MPCI	S/N Ratio of MPCI (predicted) at optimal setting
N [RPM]	F [mm/rev]	D [mm]			
605	0.06	0.6	0.461	-6.7260	-2.96944
605	0.07	0.9	0.493	-6.1431	
605	0.08	1.2	0.623	-4.1102	
787	0.06	0.9	0.574	-4.8218	
787	0.07	1.2	0.312	-10.1169	
787	0.08	0.6	0.576	-4.7916	
1020	0.06	1.2	0.513	-5.7977	
1020	0.07	0.6	0.639	-3.8900	
1020	0.08	0.9	0.602	-4.4081	

Table 3.19: Initial parameters setting for GA and ICA

GA	ICA
Population size= 70 Maximum no. of generation= 100 Selection function= Stochastic function Elite Count= 2 Crossover fraction=0.8 Crossover function= Scattered Mutation factor=0.2 Mutation function= constraint dependent	Maximum decades= 1000 Number of Countries= 80 Number of Imperialists= 8 Number of Colonies=(No Countries - No Imperialists) β= 2 γ= 0.1
No. of Parameters= 8	No. of Parameters: 5

Table 3.20: Optimal parametric combination (obtained by GA and ICA) along with fitness value(s) of the objective function(s)

Algorithm	Responses	Optimal Parametric Combination			Fitness value
		Spindle speed [RPM]	Feed Rate [mm/rev]	Depth of cut [mm]	
GA	MRR	1019.47543	0.07997	0.60169	9695.978392
	R_a	1018.19264	0.07999	1.1999	6.85972
	Fr	605	0.06	0.943	16.62534
	MPCI	1010.38508	0.07999	0.6016943	0.6433
ICA	MRR	1020	0.08	0.6	9706.22918041811
	R_a	1020	0.08	1.2	6.85241509677932
	Fr	605	0.06	0.9	16.5194921686056
	MPCI	1020	0.08	0.6	0.6449893

Table 3.21: S/N ratio table for optimizing individual response characteristics by Taguchi method

Design of Experiment			S/N Ratio of MRR	S/N Ratio of R_a	S/N Ratio of Fr
N [RPM]	f [mm/rev]	d [mm]			
605	0.06	0.6	74.1383	-21.3575	-25.1512
605	0.07	0.9	73.3286	-22.2951	-24.5962
605	0.08	1.2	76.7163	-17.2653	-25.1165
787	0.06	0.9	74.9833	-18.3013	-24.4793
787	0.07	1.2	74.2737	-19.5733	-26.5079
787	0.08	0.6	77.8827	-19.2471	-25.7659
1020	0.06	1.2	78.8873	-18.9048	-27.6847
1020	0.07	0.6	79.6431	-17.9814	-26.0275
1020	0.08	0.9	78.4569	-16.8355	-26.6714

Table 3.22: Optimal parametric combination (obtained by Taguchi Method) along with predicted S/N ratio value(s)

Optimization Methodology	Responses	Optimal Parametric Combination			Predicted S/N Ratio value(s)
		Spindle speed [RPM]	Feed Rate [mm/rev]	Depth of cut [mm]	
Taguchi's philosophy	MRR	1020	0.08	0.6	80.9446
	R_a	1020	0.08	1.2	-16.1018
	Fr	605	0.07	0.9	-24.3584
	MPCI	1020	0.08	0.9	-2.96944

3.3 Application of Fuzzy Based Harmony Search (HS) Algorithm for Parametric Optimization in Turning of CFRP (Epoxy) Composites: A Case Experimental Study

3.3.1 Coverage

The present work describes application of fuzzy logic and nonlinear regression integrated with Harmony Search (HS) algorithm for simultaneous optimization of multiple 'process performance yields' (Material Removal Rate (MRR), surface roughness (R_a) and the maximum tool tip temperature generated during operation) during machining (turning) of carbon fiber reinforced polymer (CFRP epoxy) composites. The meta-heuristic Harmony Search (HS) algorithm, which utilizes musical process of searching for a perfect state of harmony, could be found in literature as an efficient optimization technique towards determining the global optimal solution. However, the proposed fuzzy embedded HS algorithm is relatively new. A case experimental research has also been provided to exhibit its effectiveness. Results obtained thereof, have also been compared to that of Genetic Algorithm (GA).

3.3.2 Problem Definition

Existing literature focused on different methods for optimization of process parameters in a variety of manufacturing filed, production processes. Taguchi's optimization philosophy is applied mainly for single objective optimization within discrete domain of process variables; but in practice, several conflicting criterions (output responses) simultaneously may require to be optimized for selecting the best option from the number of possible choices (process environments). As traditional Taguchi approach can deal with only single objective optimization; several optimization methods such as desirability function approach (Naveen Sait et al., 2009), utility theory (Singh and Kumar, 2006), grey relation analysis (Haq et al., 2008) etc. has been proposed in combination with Taguchi philosophy for parametric appraisal and multi-objective optimization in production engineering context. But in these methods, existence of response correlation is ignored and response priority weights (for each performance characteristics) are decided by the decision-maker. PCA (Principal Component Analysis) (Datta et al., 2009) based Taguchi method can take care of response correlation; but WPCA (Weighted Principal Component Analysis) assumes accountability proportion of individual principal component as individual priority weight (Liao, 2006).

In order to avoid limitations/shortcomings of existing multi-objective optimization approaches; in the present work, fuzzy logic has been explored to aggregate multiple output responses into an equivalent single objective function called Multi-Performance Characteristic Index (MPCI). The use of fuzzy logic eliminates the necessity to assign priority weight to each response attributes.

Recently, alternative to conventional techniques, evolutionary optimization techniques are the new trend for optimization of the machining process parameters. Yusup et al. (2012a) gave an overview and the comparison of the latest five year researches from 2007 to 2011 that used evolutionary optimization techniques to optimize machining process parameter of both traditional and modern machining. The aforesaid article considered five techniques, namely genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), ant colony optimization (ACO) and artificial bee colony (ABC) algorithm. Literature found that GA was widely applied by researchers to optimize the machining process parameters. Multi-pass turning was the largest machining operation that dealt with GA optimization. In terms of machining performance, surface roughness was mostly studied with GA, SA, PSO, ACO and ABC evolutionary techniques. Though, various evolutionary techniques are being developed and widely explored to evaluate optimal machining parameters due to its ability to achieve global best values but majority of these methods invariably requires high computational time (Lee and Geem, 2005).

Yildiz (2009a) described an innovative optimization approach to solve shape optimization problems. This approach was based on two-stages which are (1) Taguchi's robust design approach to find appropriate interval levels of design parameters (2) Immune algorithm to generate optimal solutions using refined intervals from the previous stage. Yildiz (2009b) and Yildiz (2009c) presented a hybrid optimization approach based on immune algorithm and hill climbing local search algorithm for solving design and manufacturing optimization problems. The hybrid algorithm combined the exploration speed of immune algorithm with the powerful ability to avoid being trapped in local minimum of hill climbing. Yildiz (2009d) presented an optimization approach based on the particle swarm optimization algorithm and receptor editing property of immune system. The results obtained by this approach were also compared with a hybrid genetic algorithm, scatter search algorithm, genetic algorithm, and integration of simulated annealing and Hooke-Jeeves pattern search etc. Yildiz (2009e) introduced a hybrid optimization approach by combining immune algorithm and simulated annealing algorithm. Zain et al. (2011a) integrated Simulated Annealing (SA) and Genetic Algorithm (GA) to estimate optimal process parameters that lead to a minimum value of machining performance in the abrasive water jet machining. Two integration systems were proposed, labeled as integrated SA–GA-type1 and integrated SA–GA-type2. The approaches proposed in that study involved six modules, which were experimental data, regression modeling, SA optimization, GA optimization, integrated SA–GA-type1 optimization, and integrated SA–GA-type2 optimization.

Deris et al. (2011) reviewed application of Support vector machine (SVM) for machining operations.

In a reporting, Zain et al. (2011b) integrated two soft computing techniques: simulated annealing (SA) and genetic algorithm (GA) to search for a set of optimal cutting conditions value that leads to the minimum value of machining performance. Two integration systems were proposed; integrated SA–GA-type1 and integrated SA–GA-type2. The considered machining performance was surface roughness (R_a) in end milling. The proposed integration systems also reduced the number of iteration in searching for the optimal solution compared to the conventional GA and conventional SA, respectively. In another paper, Zain et al. (2011c) applied two computational approaches, Genetic Algorithm and Simulated Annealing, to search for a set of optimal process parameters value that leads to the minimum value of machining performance. The objectives of the applied techniques were: (1) to estimate the minimum value of the machining performance compared to the machining performance value of the experimental data and regression modeling, (2) to estimate the optimal process parameters values that has to be within the range of the minimum and maximum coded values for process parameters of experimental design that are used for experimental trial and (3) to evaluate the number of iteration generated by the computational approaches that lead to the minimum value of machining performance.

Zain et al. (2012) applied two modeling approaches, regression and Artificial Neural Network (ANN), in order to predict the minimum R_a (surface roughness) value of the end-milled product.

Yusup et al. (2012b) provided an overview of PSO techniques to optimize machining process parameter of both traditional and modern machining from 2007 to 2011. Machining process parameters such as cutting speed, depth of cut and radial rake angle were mostly considered by researchers in order to minimize or maximize machining performances. From the review, the most machining process considered in PSO was multi-pass turning while the most considered machining performance was production costs. Yildiz (2012a) introduced a hybrid technique based on differential evolution algorithm for solving manufacturing optimization problems. The results demonstrated superiority of the hybrid approach over other techniques like artificial bee colony algorithm, differential evolution algorithm, hybrid particle swarm optimization algorithm, hybrid artificial immune-hill climbing algorithm, hybrid Taguchi-harmony search algorithm, hybrid robust genetic algorithm, scatter search algorithm, genetic algorithm and an improved simulated annealing algorithm in terms of convergence speed and efficiency by measuring the number of function evaluations required. Yildiz and Solanki (2012) presented an efficient particle swarm-based optimization method for multi-objective optimization of vehicle crashworthiness. Durgun and Yildiz (2012) introduced Cuckoo Search Algorithm (CS) algorithm towards solving structural design optimization problems. Yildiz (2012b) presented Taguchi's robust design approach and particle swarm optimization algorithm to solve structural design optimization problems in the automotive industry. Yildiz (2013a) presented an artificial bee colony algorithm for optimal selection of cutting parameters in multi-pass turning operations. Yildiz (2013b) presented a novel hybrid optimization approach based on differential evolution algorithm and receptor editing property of immune system in order to solve optimization problems in the manufacturing industry. In another reporting, Yildiz (2013c) presented a detailed comparison of evolutionary-based optimization techniques for structural design optimization problems. Furthermore, a hybrid optimization technique based on differential evolution algorithm was introduced for structural design optimization problems. The proposed approach was applied to a welded beam design problem and the optimal design of a vehicle component to illustrate how the present approach could be applied for solving structural design optimization problems. Yildiz (2013d) introduced cuckoo search (CS) algorithm for solving manufacturing optimization problems. In order to demonstrate the effectiveness of the CS, a milling optimization problem was solved and the results were compared with those obtained using other well-known optimization techniques like, ant colony algorithm, immune algorithm, hybrid immune algorithm, hybrid particle swarm algorithm, genetic algorithm, feasible direction method, and handbook recommendation. Yildiz (2013e) presented a hybrid optimization approach based on teaching–learning based optimization (TLBO) algorithm and Taguchi's method.

Yildiz (2008) presented a novel hybrid algorithm based on harmony search algorithm and Taguchi method. This approach was applied to the case studies for turning and milling and design optimization problems. In another paper, Yildiz and Öztürk (2010) presented an optimization approach based on harmony search algorithm and Taguchi's method to solve shape optimization problems. Harmony Search (HS) algorithm is basically a meta-heuristic optimization method which has come into picture recently; which has the capability of finding optimal solution for continuous optimization problems with less computational time and few adjustment parameters.

Motivated by the wide application of algorithm based optimization, this work highlights a case experimental study to examine the effect of turning parameters viz. spindle speed, feed rate and depth of cut on different process performance features during turning of CFRP (epoxy) composites. The Material Removal Rate (MRR), Tool-Tip Temp., and surface roughness (roughness average, R_a) etc. have been considered as machining performance evaluation characteristics. Fuzzy logic has been used to aggregate these multiple responses into a single response i.e. MPCI; using nonlinear regression, a mathematical model has been established for MPCI which has been represented as a dependent function of input process variables (spindle speed, feed rate and depth of cut). Finally, HS algorithm has been applied on the derived mathematical model for MPCI in order to obtain a global optimal solution (the most favorable process environment) for turning of CFRP composites.

3.3.3 Fuzzy Inference System (FIS)

Fuzzy inference systems (FIS) pioneered by (Zadeh 1965); is a convenient way to map an input space to an output space based on a precise logic of imprecision and approximate reasoning with help of fuzzy set theory (Cox, 1992; Syunag, 2010; Abhishek et al., 2013). FIS commonly have four components: consists of a fuzzifier process, fuzzy rule base, inference engine, and a defuzzifier process (defuzzification) (Fig. 3.40).

Fuzzification: Fuzzification is a process that classifies numerical measurements into fuzzy sets. The purpose of fuzzification is to map the inputs from a set of sensors (or features of those sensors such as amplitude or spectrum) to values from 0 to 1 using a set of input membership functions.

Fuzzy rule: Fuzzy rules are a collection of linguistic statements that describe how the FIS should make a decision regarding classifying an input or controlling an output. In fuzzy rule, there are consists of IF-THEN form which is expressed the relation between machining parameters and machining performance.

Inference Engine: An inference engine applies the rule base to the fuzzy sets to obtain a fuzzy outcome.

Defuzzification: Defuzzification is the conversion of a fuzzy quantity to a precise quantity, fuzzification that is the conversion of a precise quantity to a fuzzy quantity.

3.3.4 Harmony Search Algorithm

Harmony search (HS) algorithm is firstly proposed by Zong Woo Geem in 2001. It is meta-heuristic algorithm which is based on natural musical performance processes that occur when a musician searches for a better state of harmony, such as during jazz improvisation. In the HM algorithm, each musician served as a decision variable which plays note i.e. treated as a value to find a best harmony, that supposed to obtain global optimal solution

(Lee and Geem, 2004; Saka, 2009, Manjarres et al., 2013). Following are the steps involved in Harmony search algorithm:

Step 1: Initialize the problem and algorithm parameters:

At first, define the optimization problem as (Eq. 3.33).

Objective function,

$$\min f(y) \tag{3.33}$$

Subjected to $y_i \in Y_i \qquad i = 1,2,3,...n$

where, y = set of decision variables

n = no. of decision variables

Y_i = possible range of values for each decision variable

In HS algorithm some parameters has to be initialize first, which are as follows:

- Harmony memory size (HMS): it is the size of the harmony memory.
- Harmony Memory Considering Rate (HMCR): it is the rate of selection of a value from the harmony memory.
- Pitch Adjusting Rate (PAR): the rate of selection of a neighbouring value.
- Stopping criteria.

Step 2: Initialize the harmony memory (HM).

$$HM = \begin{bmatrix} y_1^1 & y_2^1 & \cdots & y_n^1 \\ y_1^2 & y_2^2 & \cdots & y_n^2 \\ \vdots & \vdots & \vdots & \vdots \\ y_1^{HMS} & y_2^{HMS} & \cdots & y_n^{HMS} \end{bmatrix} \tag{3.34}$$

Step 3: Generation of a new harmony vector from the HM.

New harmony vector is given as (Eq. 3.35)

$$y' = (y'_1, y'_2, \ldots, y'_i) \tag{3.35}$$

It can be improvises by using three rules, which are memory consideration, pitch adjustment and by the random selection as (Eq. 3.36).

$$y' \rightarrow \begin{cases} y' \in \{y_i^1, y_i^2, \ldots, y_i^{HMS}\} & \text{with probability HMCR} \\ y' \in Y_i & \text{with probability } (1-\text{HMCR}) \end{cases} \tag{3.36}$$

Now, every element selected by harmony consideration is checked for pitch adjustment.

Pitch adjusting decision for y' is given as (Eq. 3.37).

$$y' \leftarrow \begin{cases} \text{Yes} & \text{for probability PAR} \\ \text{No} & \text{for probability } (\text{PAR}-1) \end{cases} \tag{3.37}$$

Here, for the value of (PAR-1) sets no modification is done in y' and if the pitch adjustment decision is yes then modification is done as per the (Eq. 3.38).

$$y' = y' + \text{rand}() \times b \tag{3.38}$$

where, b = arbitrary distance band width

$\text{rand}()$ = random number varies between 1 to 0.

Pitch adjusting rate for improvisation of I is given by (Eq. 3.39).

$$\text{PAR}(I) = \text{PAR}_{\min} + \frac{\text{PAR}_{\max} - \text{PAR}_{\min}}{N} \times I \tag{3.39}$$

where, $I = 1, 2, \ldots, N$

N = no. of improvisation

$\text{PAR}_{\min}$ = minimum pitch adjustment rate

$\text{PAR}_{\max}$ = maximum pitch adjustment rate

Bandwidth b is depending upon the variance of the population in each improvisation and it is adjusted as per the (Eq. 3.40).

$$b(I) = \sqrt{\text{var}(Y)} \tag{3.40}$$

Step 4: Update the HM.

If the New Harmony is better than previous memory in the HM which can be judged in terms of objective function value (fitness function value), then the previous harmony (worst harmony) is replaced by New Harmony in existing HM.

Step 5: Repeat Steps 3 and 4 until maximum number of improvisations is reached, then stop.

3.3.5 Experimentation

The experiments were carried out on manually operated lathe of series HMT NH26 (manufactured by HMT Machine Tools Kalamasarry, India). The turning operation was performed on sample of carbon fibered reinforced epoxy bars $(\phi 50 \times 150)$ and 60^0 fiber orientations (prepared by hand layup). The specimens contained 30% carbon fiber and 70% epoxy resin. Tunable Tooling System (TTS) (100280902, H694978921000) with the Kennametal TTS System (SNMG 120408, H391204081156), (Manufactured by WIDIA) was used as tool material during experimentation.

The Design of Experiment (DOE) is an efficient procedure for planning of experiments so as to analyze the influence of process parameters on machining performances to yield valid and objective conclusions. In the context of machining (turning operation); based on aforesaid literature review, it has been found that spindle speed, depth of cut and feed rate are the common machining parameters which affects machining and machinability aspects of composites. In the present work, a Central Composite Design (CCD) has been considered for the entire experimentation. CCD comprises of imbedded factorial or fractional factorial design with center points that is augmented with a group of 'star points' which allows assessment of curvature. In this experimentation rotatable central composite design has been selected, since it has been widely used for modeling of second order response surface as documented in literature. Rotatability refers to the uniformity for predication of errors and in this design; all the points at same radial distance (r) from the centre line have same magnitude of prediction error. For the given variable, to achieve the rotatability α has been required as computed $\alpha = (n_f)^{1/4}$ where n_f is number of points in 2^k factorial design.

Total 20 numbers of experimental runs, (eight factorial points (2^3), six axial points (2×3) and six center runs) have been performed in this experimentation. The machining parameters such as spindle speed, feed rate and depth of cut have been varied at three different levels as listed in Table 3.23. Tables 3.24a, b show the experimental design matrix consisting of experimental run order and experimentally observed values of machining performance features.

Surface roughness is an important criterion for determining surface quality in machining process. It can result due to the movement of cutting tool tip repetitively along the work piece at the given feed rate during machining process. Mitutoyo Surf Test (SJ -210) has been used to assess the roughness average (R_a) in the direction of the tool movement. R_a value has been determined in three different places of the finished job and average of these three has been considered for a particular set of experiment.

In any machining operation, Material Removal Rate (MRR) is another important criterion which depicts performance extent of the particular machining operation. It can be evaluated as ratio of volume of material removed during operation w.r.t. machining time. Following equation is used for determination of MRR:

$$MRR = \frac{W_i - W_f}{\rho \times t_m} \; mm^3/min \tag{3.41}$$

W_i initial weight of work piece

W_f final weight of work piece

ρ density of work piece (0.0015 gm/mm^3)

t_m Machining time

During machining operation, temperature arises at machined surface because of plastic deformation of the work piece surface, the friction of the chip on the tool tip and the friction between the tool and the work-piece interface. Hence, tool manufacturers emphasize to measure the tool tip temperature, as tool wear is a function of the temperature to which the tool is subjected. In the present work, tool-tip temperature has been measured by using non-contact infrared thermometer (Model: AR882 and temperature range -18 to 1500^0C), supplied by Real Scientific Engineering Corporation, New Delhi, INDIA. Infrared thermometer measures the surface temperature of an object. The unit's optics sense emitted, reflected and transmitted energy which is collected and focused onto a detector. The unit's electronics translate the information into a temperature reading which is displayed on the unit. For increased ease and accuracy the laser pointer makes aiming even more precise.

The experimental data in relation to MRR, Tool-Tip Temp and roughness average for each experimental run has been furnished in Table 3.25.

3.3.6 Results and Discussions

In this experimentation, the effect of machining process parameters such as spindle speed, feed rate and depth of cut has been determined on process output features like MRR, Tool-Tip Temp and R_a. The study also attempts to determine a global optimal solution for simultaneous optimization of multiple process responses during turning of CFRP composites. The flowchart for Fuzzy-HS to obtain optimal parametric combination (global solution) has been provided in Fig. 3.41.

3.3.6.1 ANOVA Results

Analysis of Variance (ANOVA) is a statistical tool performed to evaluate the degree of significant effect of machining variables on output performance characteristics. It explores P-value called the probability of significance. If P-value for a term/source (individual factor or factorial interaction) appears less than 0.05; it is said that the effect of that term/source is significant (on influencing the particular response) at 95% confidence level.

The P value for parameters which are likely to affect more significantly on MRR, tool-tip temperature and surface roughness has been found less than 0.05. From ANOVA analysis, it is apparent that for maximizing the MRR, the most significant parameter is depth of cut (Table 3.26). The value of R- square for MRR is 92.47%. For minimizing the surface roughness, depth of cut and feed rate are more influential parameters (Table 3.27). The value of R- square for surface roughness is 91.82%. Similarly, for minimizing the Tool-Tip Temp., the significant parameters are spindle speed and depth of cut (Table 3.28). The value of R- square for Tool-Tip Temp. is 90.54%.

3.3.6.2 Optimization

For the multi-objective optimization, it is necessary to aggregate individual outcomes (MRR, surface roughness, tool-tip temp.) into a single objective function. In order to develop a single objective function, fuzzy logic has been used in which multiple objectives (responses) have been clubbed into an equivalent single response i.e. MPCI. In doing so, initially, all the output responses (i.e. MRR, surface roughness and tool-tip temp.) have been normalized so that for all cases the normalized values come within the range 0 to 1 (where 0 denotes as worst value and 1 denotes best value) (Table 3.29). The formulas for normalization have been presented below.

For, surface roughness and tool-tip temp., (Smaller-is-Better criterion):

$$y_{ij} = \frac{x_{ij} - \max x_{ij}}{\min x_{ij} - \max x_{ij}} \qquad (3.42)$$

For, MRR (Higher-is-Better criterion):

$$y_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{3.43}$$

where, x_{ij} is experimental value, whereas, $\max x_{ij}$ is the maximum value $\min x_{ij}$ is minimum observed value.

The relationship between the dependent variable and a set of independent variable is determined by using nonlinear regression equation. In contrast to traditional linear regression, which is constrained to estimating linear models, nonlinear regression can estimate models with arbitrary relationships between independent and dependent variables. This is accomplished using iterative estimation algorithms. The proposed mathematical model for response is represented as below:

$$MPCI = C \times N^{a} \times f^{b} \times d^{c} \tag{3.44}$$

Here C represents the constant; N represents spindle speed; f represents feed rate; d is the depth of cut. a, b, c are estimated coefficients of the said regression model. In the present work, Gauss-Newton algorithm has been used to generate the coefficients.

The mathematical model derived for MPCI is given as follows:

$$\mathrm{MPCI} = 0.010 \times \mathrm{N}^{0.138} \times \mathrm{f}^{(-.782)} \times \mathrm{d}^{0.914} \qquad (R^2 = 95.6\%) \tag{3.45}$$

In calculating MPCI, in FIS system (Fig. 3.42), three membership functions (Figs. 3.43-3.45) have been assigned to each of the input variables viz. (i) Normalized value of MRR (ii) Normalized value of tool-tip temp. (iii) Normalized value of R_a. The selected membership functions for individual input variables are: “Low”, “Medium”, and “High”; whereas for MPCI, five membership functions have been assigned: “Very Small, “Small”, “Medium”, “Large”, and “Very Large” (Fig. 3.46). Fuzzy logic converts linguistic inputs into linguistic output by exploring a given rule-base (Fig. 3.47; Table 3.30). Linguistic output is again converted to numeric values (MPCI) by defuzzification method (Table 3.31).

To obtain a rule,

$$R_i : \text{if } x_1 \text{ is } A_{i1}, x_2 \text{ is } A_{i2}, \text{and } x_s \text{ is } A_{iM} \tag{3.46}$$

$$\text{Then}, y_i \text{ is } C_i,$$

Here M is the total number of fuzzy rules. $x_j (j = 1,2,,........,s)$ are the input variables, y_i are the output variables and A_{ij} and C_i are fuzzy sets modeled by the membership functions $\mu_{Aij}(x_j)$ and $\mu_{Ci}(y_i)$, respectively. Based on the Mamdani implication method of inference reasoning for a set of disjunctive rules, the aggregated output for the M rules is

$$\mu_{Ci}(y_j) = \max\{\min[\mu_{Ai1}(x_1), \mu_{Ai2}(x_2),......, \mu_{Ais}(x_s)]\}, \qquad i = 1,2,........, M \tag{3.47}$$

Using a defuzzification method, fuzzy values can be combined into one single crisp output value. The centre of gravity, one of the most popular methods for defuzzifying fuzzy output functions, is employed and calculated as follows:

$$\hat{y}_i = \frac{\int y_i \mu_{ci}(y_i) dy}{\int \mu_{ci}(y_i) dy} \tag{3.48}$$

The fitness function which has been derived by using non regression analysis on MPCI (Eq. 3.45) has been used to generate global optimal solution with the help of Harmony Search algorithm (parameters setting in HS algorithm have been shown in Table 3.32). Fig. 3.48 shows the convergence plot for the result of the Harmony search method. The global optimal value is 0.7102 with optimal combination comes (N = 777.6735 RPM; f = 0.0500 mm/rev; d = 3.0000 mm).

3.3.6.3 Comparison with GA

A comparative analysis has also been made to check application potential of aforesaid fuzzy based HS in comparison with GA. Table 3.33 represents initial parameter settings for GA. The fitness function of MPCI (Eq. 3.45) has been optimized using GA. The global optimal value appears as 0.698938149 with optimal combination obtained as (N = 712.9100283 RPM; f = 0.05041 mm/rev; d = 2.99997 mm) by using GA. Fig. 3.49 shows convergence plot of MPCI function by using GA. As compared to the result of HS, it is evident that HS provides more accurate result (N = 777.6735 RPM; f = 0.0500 mm/rev; d = 3.0000 mm) as well as better fitness value i.e. 0.7102. However, as per availability of factorial values in the machine/setup the optimal has to be adjusted at (N = 787 RPM; f = 0.0500 mm/rev; d = 3.0000 mm).

3.3.7 Concluding Remarks

Despite of increased applications of composite materials in aerospace applications, defense, medical equipment, auto industry etc., due to their exceptional physical and mechanical properties; the machining of composites materials remains a challenge. Fiber reinforced composites are very much prone to different types of damages during machining process such as delamination, fiber pullout, micro-cracks, thermal damages etc. Optimization of the machining process parameters may evidently reduce the probability of these damages.

Therefore, it is essential to evaluate optimal machining condition to improve material removal rate, surface roughness and reduce Tool-Tip Temp. during turning of CFRP (epoxy) composites. In this context, a unified attempt has been made towards simultaneous optimization of aforesaid machining performance characteristics by using fuzzy logic, nonlinear regression coupled with Harmony Search optimization algorithm. Experiments have been conducted based on Central Composite Design (CCD) considering three controllable process parameters such as spindle speed, feed rate and the depth of cut. The output responses such as Material Removal Rate (MRR), surface roughness (R_a) and the maximum tool tip temperature generated during operation have been determined for each of the experimental run. Analysis of Variance (ANOVA) has also been performed in order to determine significant factors that are likely to impose major influence on aforesaid process output characteristics. Fuzzy logic has been implemented to aggregate multiple output responses into an equivalent single objective function i.e. Multi-Performance Characteristics Index (MPCI). Nonlinear regression analysis has been performed for developing a mathematical model of MPCI (represented as a function of input process parameters) which acted as an objective function in the proposed Harmony search optimization algorithm. Results revealed that in comparison with GA, the proposed fuzzy based Harmony Search algorithm is an effective approach towards parametric appraisal and simultaneous optimization of process output responses during turning of CFRP composites.

The contributions of the aforesaid case experimental research have been pointed out below.

- ANOVA has been performed to assess the significant process parameters which affect Material Removal Rate (MRR), surface roughness and Tool-Tip Temp. It has been observed that depth of cut is the most influencing parameter on these output characteristics as compared to spindle speed as well as feed rate.
- A mathematical model for MPCI has been formulated by using by using nonlinear regression analysis. Fuzzy logic has then been used to aggregate the aforesaid characteristics (multiple outputs) into a single objective function i.e. MPCI. In this aggregation, existences of response correlation need not to be checked. Moreover, assignment of response priority weight need not be required in this approach. Global optimal solution has been determined by the Harmony Search algorithm.

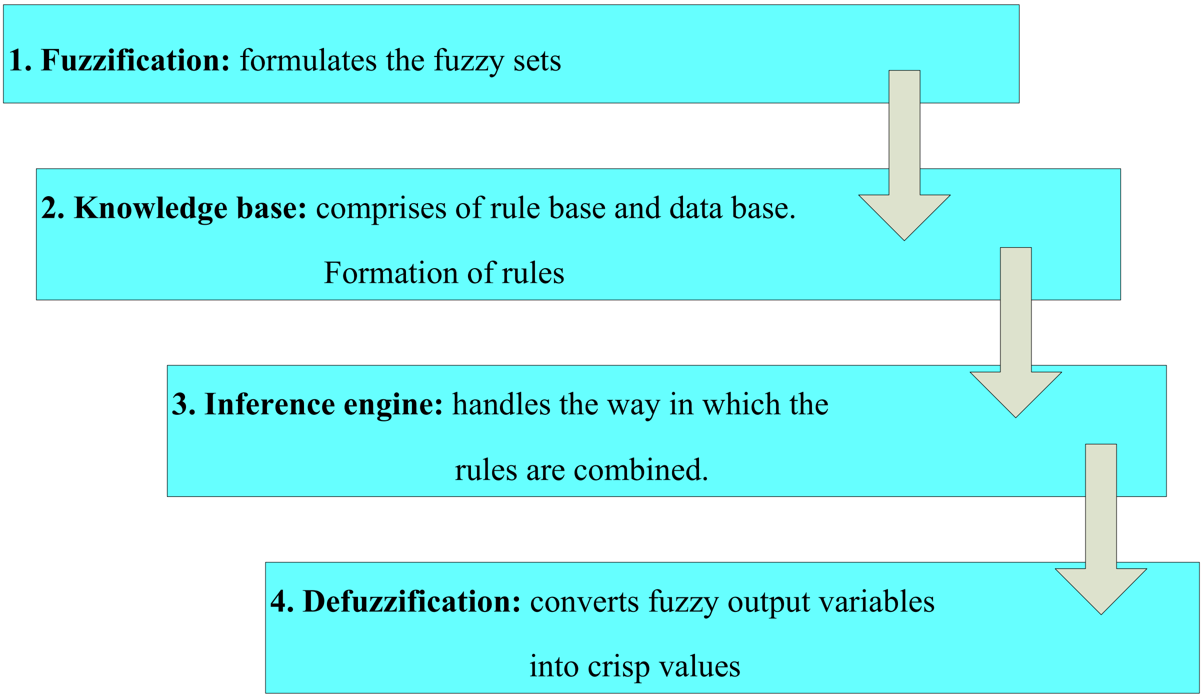


Fig. 3.40: Fuzzy Inference System (FIS)

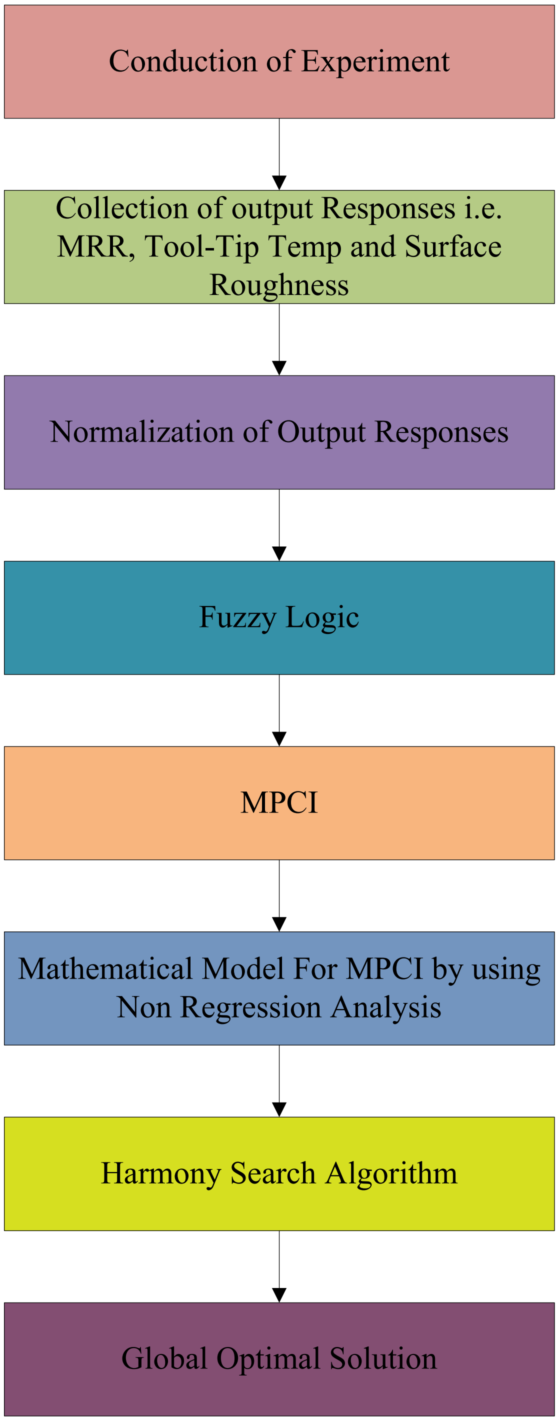


Fig. 3.41: Flowchart for Fuzzy-HS to obtain optimal combination

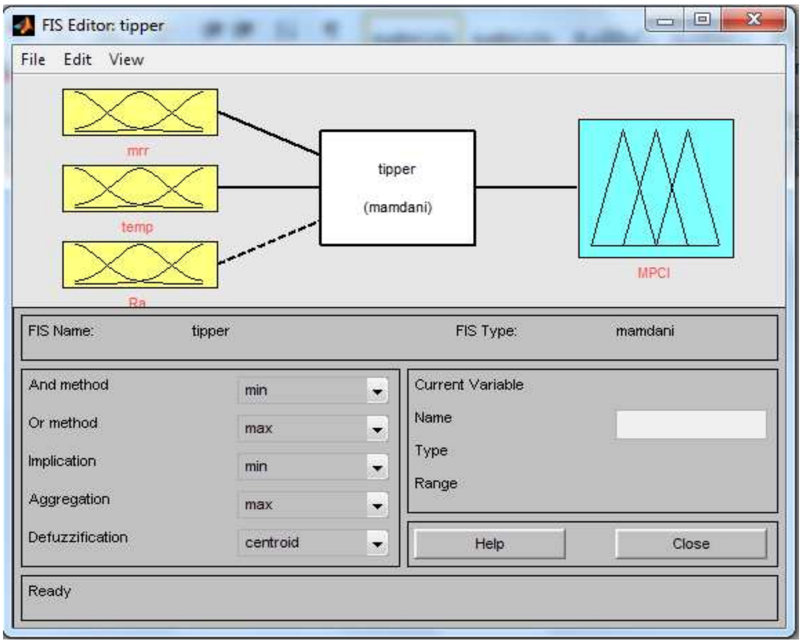


Fig. 3.42: Fuzzy Inference system

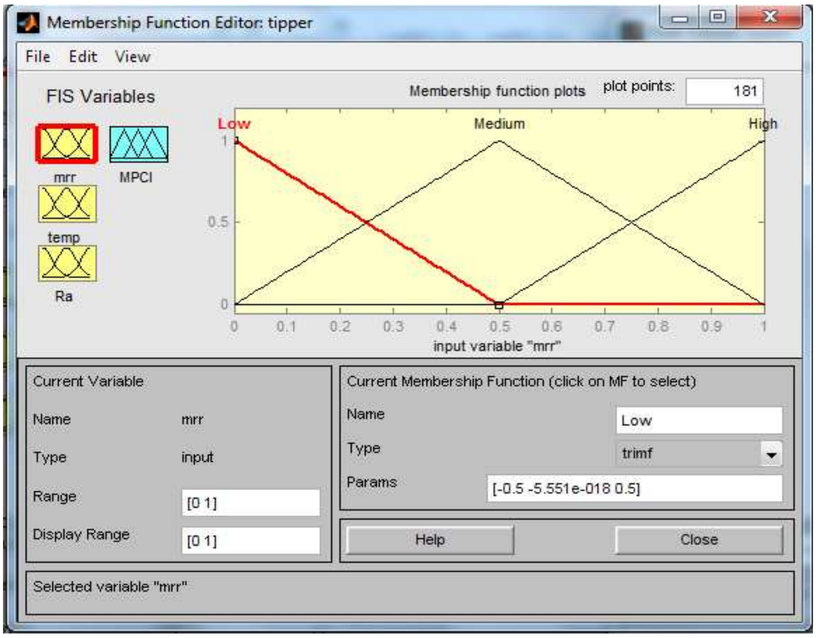


Fig. 3.43: Membership function for MRR

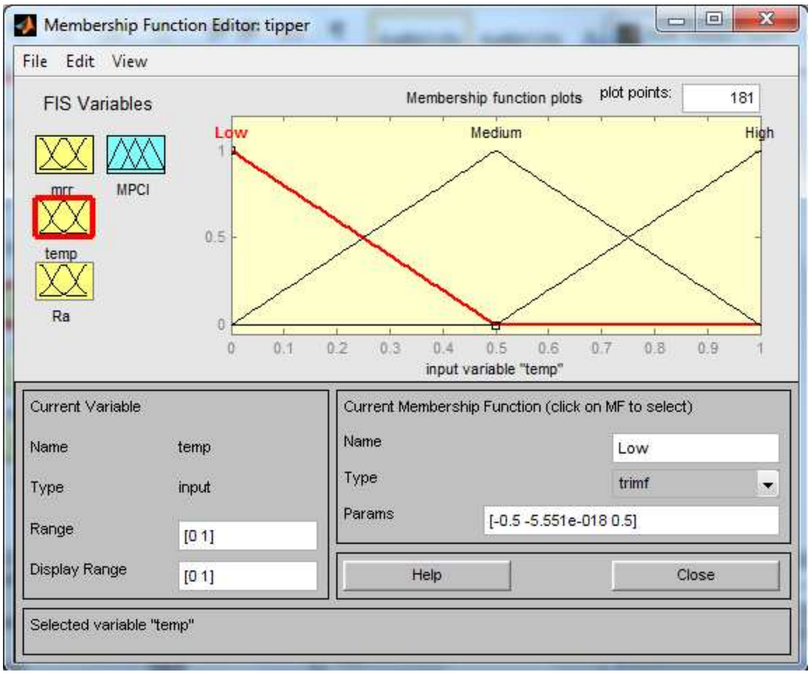


Fig. 3.44: Membership function for Tool-tip temperature

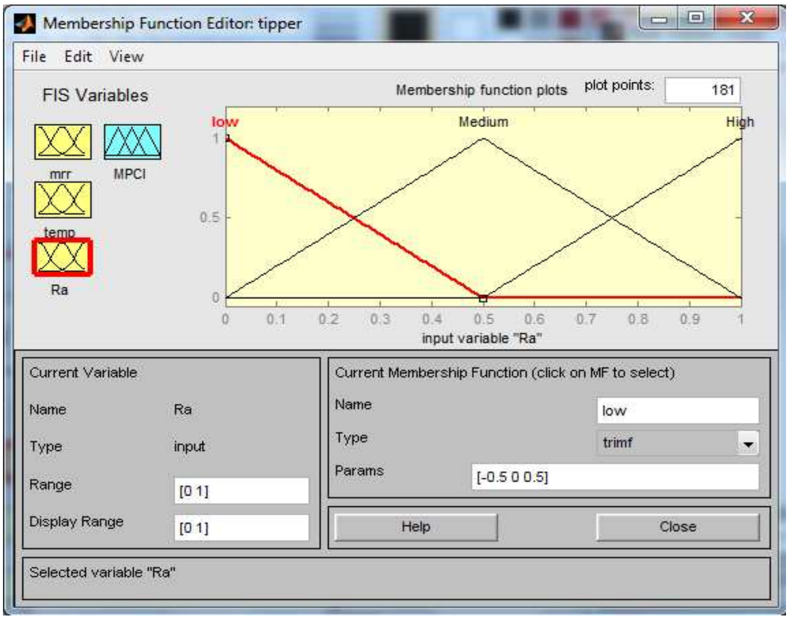


Fig. 3.45: Membership function for surface roughness

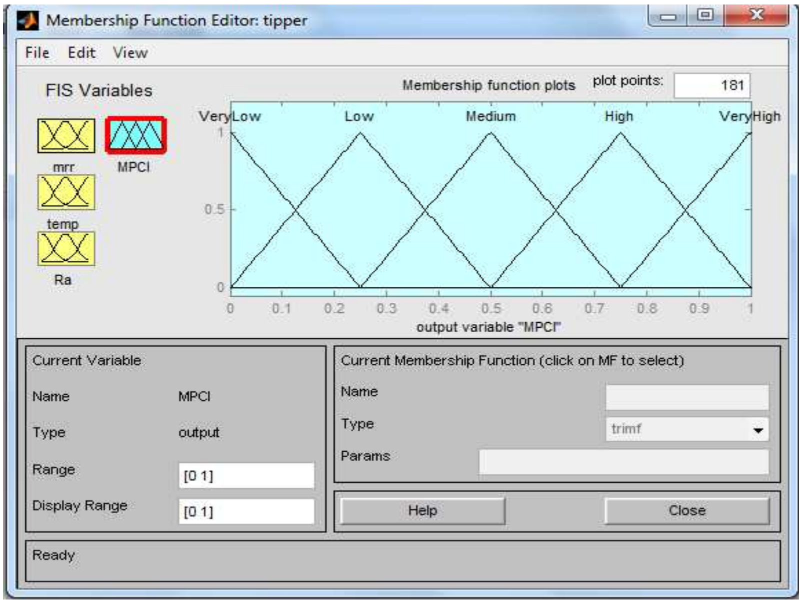


Fig. 3.46: Membership function for MPCI

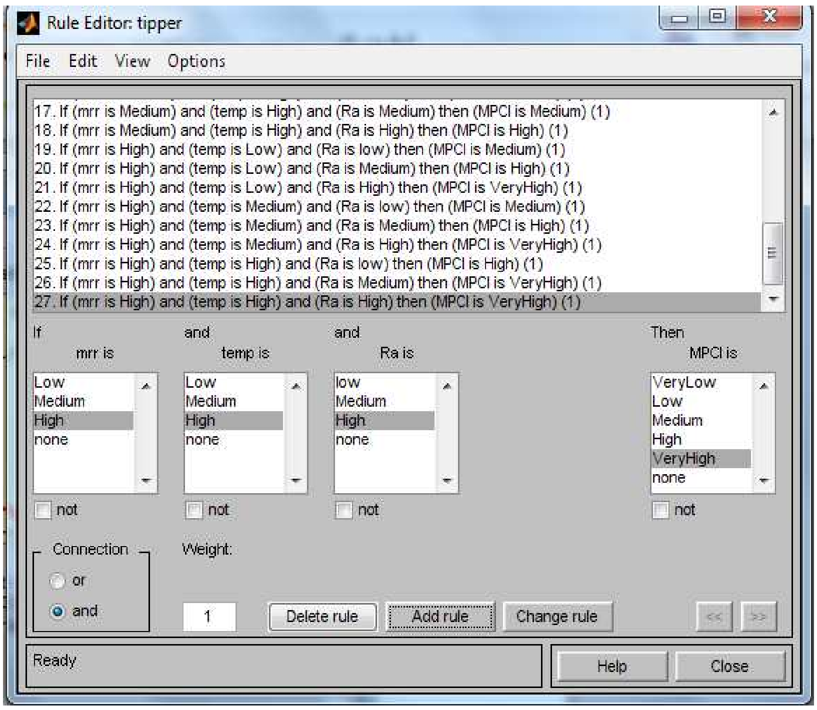


Fig. 3.47: Fuzzy rule editor

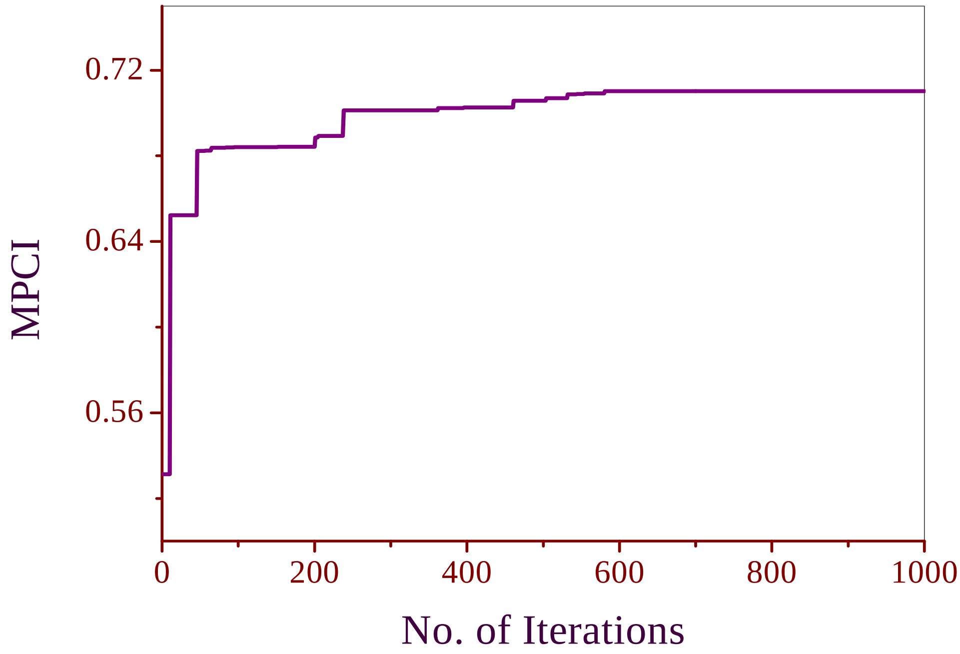


Fig. 3.48: Convergence plot of MPCI by HS

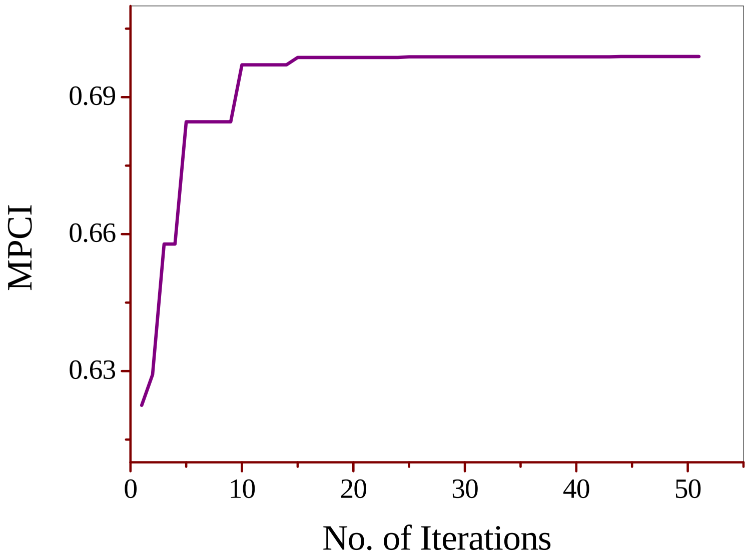


Fig. 3.49: Convergence plot of MPCI by GA

Table 3.23: Domain of experiment

Sl. No.	Process parameters	Notation	Unit	Level (-1)	Level (0)	Level (+1)
1	Spindle Speed	N	[RPM]	420	605	787
2	Feed Rate	f	[mm/rev]	0.05	0.06	0.07
3	Depth of Cut	d	[mm]	2	2.5	3

Table 3.24a: Design of experiment by using Central Composite Design (Coded Form)

Std Order	Run Order	Pt Type	Blocks	N	f	d
1	1	1	1	-1	-1	-1
2	2	1	1	1	-1	-1
3	3	1	1	-1	1	-1
4	4	1	1	1	1	-1
5	5	1	1	-1	-1	1
6	6	1	1	1	-1	1
7	7	1	1	-1	1	1
8	8	1	1	1	1	1
9	9	-1	1	-1	0	0
10	10	-1	1	1	0	0
11	11	-1	1	0	-1	0
12	12	-1	1	0	1	0
13	13	-1	1	0	0	-1
14	14	-1	1	0	0	1
15	15	0	1	0	0	0
16	16	0	1	0	0	0
17	17	0	1	0	0	0
18	18	0	1	0	0	0
19	19	0	1	0	0	0
20	20	0	1	0	0	0

Table 3.24b: Design of experiment by using Central Composite Design (natural values)

Std. Order	Run Order	Pt. Type	Blocks	Spindle Speed [RPM]	Feed Rate [mm/rev]	Depth of Cut [mm]
1	1	1	1	420.0	0.05	2.0
2	2	1	1	787.0	0.05	2.0
3	3	1	1	420.0	0.07	2.0
4	4	1	1	787.0	0.07	2.0
5	5	1	1	420.0	0.05	3.0
6	6	1	1	787.0	0.05	3.0
7	7	1	1	420.0	0.07	3.0
8	8	1	1	787.0	0.07	3.0
9	9	-1	1	420.0	0.06	2.5
10	10	-1	1	787.0	0.06	2.5
11	11	-1	1	603.5	0.05	2.5
12	12	-1	1	603.5	0.07	2.5
13	13	-1	1	603.5	0.06	2.0

14	14	-1	1	603.5	0.06	3.0
15	15	0	1	603.5	0.06	2.5
16	16	0	1	603.5	0.06	2.5
17	17	0	1	603.5	0.06	2.5
18	18	0	1	603.5	0.06	2.5
19	19	0	1	603.5	0.06	2.5
20	20	0	1	603.5	0.06	2.5

N.B: As 603.5 RPM was not available in the machine/setup; 605 RM has been taken instead of 603.5 RPM

Table 3.25: Experimental data

Sl. No.	MRR [mm^3/min]	Tool-Tip Temp [^{0}C]	R_a [µm]
1	9651.403053	58.7	10.3503
2	5436.847	76.6	11.919
3	2739.632	54.8	5.9303
4	5812.170899	85.2	10.9967
5	10837.83243	72.3	4.391
6	7398.520296	96	2.534
7	3505.965474	83.9	10.1457
8	14637.07259	116.7	9.3103
9	12824.10185	83.1	7.272
10	14050.52323	114.7	6.0723
11	13557.28854	103	8.1947
12	10504.56575	103.4	9.345
13	2426.18143	63.4	11.876
14	7198.560288	103.3	6.027
15	12477.5045	125.3	7.5627
16	14130.50723	118.2	8.534
17	14650.40325	109.4	9.648
18	15010.33127	109.8	9.0707
19	15463.57395	97.8	8.283
20	13863.89389	118.7	9.2577

Table 3.26: ANOVA for MRR

Source	DOF	Sum of square of source	Mean sum of square of source	P value
N	1	6046927	6046927	0.176
f	1	9375051	9375051	0.100
d	1	30666022	30666022	0.008
N*N	1	52451528	4390890	0.242
f*f	1	26973045	56065	0.891
d*d	1	149020677	149020677	0.000
N*f	1	59718866	59718866	0.001
N*d	1	9754530	9754530	0.094
f*d	1	5189245	5189245	0.207
Lack of fit	5	22932078	4586416	0.072
Pure Error	5	5514742	1102948	
Total	19	377642711		

Table 3.27: ANOVA for surface roughness

Source	DOF	Sum of square of source	Mean sum of square of source	P value
N	1	0.752	0.752	0.386
f	1	6.954	6.954	0.020
d	1	34.836	34.836	0.000
N*N	1	3.940	7.0158	0.020
f*f	1	1.830	0.6887	0.406
d*d	1	1.279	1.2795	0.265
N*f	1	2.253	2.253	0.126
N*d	1	10.875	10.875	0..06
f*d	1	39.932	39.932	0.000
Lack of fit	5	6.331	1.2662	0.200
Pure Error	5	2.838	0.5676	
Total	19	112.21		

Table 3.28: ANOVA for Tool-tip temperature

Source	DOF	Sum of square of source	Mean sum of square of source	P value
N	1	1860.50	1860.50	0.001
f	1	139.88	139.88	0.221
d	1	1782.22	1782.22	0.001
N*N	1	115.86	115.86	0.262
f*f	1	13.20	13.20	0.697
d*d	1	1335.95	1335.95	0.002
N*f	1	58.32	58.32	0.419
N*d	1	8.40	8.40	0.755
f*d	1	95.22	95.22	0.306
Lack of fit	5	354.58	70.92	0.613
Pure Error	5	464.82	92.96	
Total	19	8661.07		

Table 3.29: Normalized value of output responses

Sl. No.	MRR	Tool tip Temperature	R_a
1	0.554192	0.944681	0.16715
2	0.230926	0.69078	0
3	0.024042	1	0.638114
4	0.259714	0.568794	0.098274
5	0.645194	0.751773	0.802131
6	0.381391	0.415603	1
7	0.082822	0.587234	0.18895
8	0.936606	0.121986	0.277965
9	0.797546	0.598582	0.495152
10	0.891616	0.150355	0.622983
11	0.853783	0.316312	0.396835
12	0.619632	0.310638	0.274267
13	3.3E-08	0.878014	0.004582
14	0.366053	0.312057	0.62781
15	0.770961	0	0.464177
16	0.897751	0.100709	0.360682
17	0.937628	0.225532	0.241982
18	0.965235	0.219858	0.303495
19	1	0.390071	0.387427
20	0.877301	0.093617	0.28357

Table 3.30: Fuzzy rule matrix

Sl. No	MRR	Tool tip temperature	R_a	MPCI
1	Small	Small	Small	Very small
2	Small	Small	Medium	Small
3	Small	Small	Large	Medium
4	Small	Medium	Small	Very small
5	Small	Medium	Medium	Small
6	Small	Medium	Large	Medium
7	Small	Large	Small	Small
8	Small	Large	Medium	Small
9	Small	Large	Large	Medium
10	Medium	Small	Small	Small
11	Medium	Small	Medium	Medium
12	Medium	Small	Large	Large
13	Medium	Medium	Small	Small
14	Medium	Medium	Medium	Medium
15	Medium	Medium	Large	Large
16	Medium	Large	Small	Medium
17	Medium	Large	Medium	Medium
18	Medium	Large	Large	Large
19	Large	Small	Small	Medium
20	Large	Small	Medium	Large
21	Large	Small	Large	Very large
22	Large	Medium	Small	Medium
23	Large	Medium	Medium	Large

24	Large	Medium	Large	Very large
25	Large	Large	Small	Large
26	Large	Large	Medium	Large
27	Large	Large	Large	Very large

Table 3.31: MPCI values as obtained from FIS

Sl. No.	Computed MPCI values
1	0.503
2	0.324
3	0.349
4	0.289
5	0.652
6	0.681
7	0.267
8	0.591
9	0.647
10	0.692
11	0.587
12	0.459
13	0.242
14	0.497
15	0.606
16	0.595
17	0.578
18	0.615
19	0.684
20	0.559

Table 3.32: Parameter settings for Harmony Search

Parameters	**Value assigned**
Maximum No. of iterations	1000
harmony memory size	6
harmony consideration rate (HMCR)	0.9
minimum pitch adjusting rate (PARmin)	0.4
maximum pitch adjusting rate (PARmax)	0.9
minimum bandwidth (bwmin)	0.0001
maximum bandwidth (bwmax)	1

Table 3.33: Initial parameters setting for GA

GA
Population size= 70 Maximum no. of generation= 100 Selection function= Stochastic function Elite Count= 2 Crossover fraction=0.8 Crossover function= Scattered Mutation factor=0.2 Mutation function= constraint dependent

3.4 Optimization of MRR, Surface Roughness and Maximum Tool-Tip Temperature during Turning of CFRP (Epoxy) Composites: Application Potential of PCA-Fuzzy-Taguchi Integrated Approach

3.4.1 Coverage

Recently, machining of carbon fiber reinforced polymer (CFRP) composites has become a vital concern for the modern manufacturing companies due its widespread applications especially in automobile as well as aerospace industries. Owing to the necessity of mass-production of CFRP component parts, it is indeed essential to optimize the machining process parameters in order to improve process performance yields in terms of product quality economically. Overall performance of the machining (turning) process is influenced by different process parameters such as spindle speed, feed rate and depth of cut. In machining of CFRP composites, material removal rate, surface roughness and tool tip temperature are generally considered as the output responses. In the present work, the extent of process performance has been evaluated in turning of CFRP composites using PVD coated carbide tool. For optimization of multiple responses, a Fuzzy Inference System (FIS) has been used to convert multiple responses into an equivalent single response known called as Multi- Performance Characteristic Index (MPCI). A non-linear regression model has been developed in expressing MPCI as a function of the selected process parameters. The said regression model has been considered as the fitness function and finally optimized by two evolutionary techniques known as harmony Search (HS) algorithm and Teaching-Learning-Based Optimization (TLBO) algorithm. The effectiveness of the aforesaid algorithm has been compared to that of Taguchi’s robust optimization philosophy.

3.4.2 Problem Definition

The appropriate selection of machining parameters, like cutting speed, feed rate, depth of cut, (with respect to a particular work piece-tool material) is the critical issue in turning process. The ranges of cutting parameters are chosen from machining databases (which depends on maximum or minimum limit of machine specification). Thus, a variety of combinations of process parameters can be fixed in the machine/set up; but these values are not the optimal. Hence, the optimization of machining process parameters is essentially required to achieve compatible balance between quality and productivity which include high production rate with reduced cost as well as to maintain good surface finish and dimensional accuracy. During machining, it is aimed at obtaining a global optimal machining condition;

but the objective function may be multimodal i.e. have many local minimum or maximum. Since classical optimization methods are mostly single point gradient-based search techniques, they cannot explore the optimization landscape effectively. Hence, evolutionary algorithms are applied to overcome their limitation. The most commonly evolutionary techniques are genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), ant colony optimization (ACO), harmony search (HS), and teaching learning based optimization (TLBO) and efficiently used in various fields such as industrial planning, scheduling, decision making and pattern recognition etc.

Hence, this part of work highlights application of (i) teaching learning based optimization (TLBO), and (ii) harmony search (HS) algorithm in order to evaluate optimal machining condition in turning of CFRP (epoxy) composites. In this study, the performance measurement characteristics viz. MRR, surface roughness and maximum tool-tip temperature have been evaluated. PCA has been applied to check correlation among the aforementioned responses and to convert these correlated indices into uncorrelated indices known as principal components. Further, these individual principal components have been aggregated into a single response i.e. MPCI using fuzzy inference system (FIS). A non-linear regression model has been developed for MPCI as a function of of turning process parameters and treated as objective function. Finally, optimal solution has been obtained by implantation of HS and TLBO. The effectiveness of the aforesaid algorithms has been compared to the result of Taguchi's optimization philosophy.

3.4.3 Experimentation

The present study focuses on selection of appropriate process environment (parameters setting) to minimize surface roughness and cutting tool-tip temperature (generated during machining) as well as to maximize MRR in turning of carbon fiber reinforced polyester composites. The experimental layout has been demonstrated in Fig. 3.50. The conventional process parameters such as spindle speed, feed rate and depth of cut have been considered as inputs in this experimental work. Aforementioned parameters have been varied into five discrete levels (Table 3.34). Taguchi's L_{25} orthogonal array (Table 3.35) experimental layout has been chosen for experimentation.

The experiments have been carried out on lathe of series HMT NH26 (manufactured by HMT Machine Tools Kalamasarry, India). The turning operations have been performed on sample of CFRP epoxy composite bars (ø50x150 mm) (Density: 1.1gm/cm^3, Composition: 30% fibre and 70% epoxy, fibre orientation 60^0). PVD coated carbide tool (Tunable Tooling System (TTS) (100280902, H694978921000) with the Kennametal TTS System (SNMG

120408, H391204081156), (Manufactured by WIDIA) was used as tool material during experimentation.

Mitutoyo Surf Test (SJ-210) has been used to assess the roughness average (R_a) in the direction of the tool movement. The R_a values of the machined samples have been measured at three different locations and average of the three measurements has been considered for a particular set of experiment.

Following equation is used for determination of MRR:

$$MRR = \frac{(W_i - W_f)}{\rho . t_m} \frac{mm^3}{min} \tag{3.49}$$

W_i = Initial weight of the work piece, W_f = Final weight of the work piece, ρ = Density of the work material, t_m = Machining time.

During machining operation, temperature arises at machined surface because of plastic deformation of the work piece surface, the friction of the chip on the tool tip and the friction between the tool and the work-piece interface. Hence, emphasize must be made to reduce the tool tip temperature, as tool wear is a function of the temperature to which the tool is subjected. In the present work, tool-tip temperature has been measured by using non-contact infrared thermometer (Model: AR882 and temperature range -18 to 1500 ^{0}C), supplied by Real Scientific Engineering Corporation, New Delhi. Infrared thermometer measures the surface temperature of an object. The unit's optics sense emitted, reflected and transmitted energy which is collected and focused onto a detector. The unit's electronics translate the information into a temperature reading which is displayed on the unit. For increased ease and accuracy the laser pointer makes aiming even more precise. Table 3.36 represents the experimental data.

3.4.4 Results and Discussions

3.4.4.1 Conversion of multi-response features into a single response (MPCI)

The present study aims to optimize MRR, surface roughness and tool-tip temperature during turning of CFRP composites. An appropriate machining condition (parameters setting) has been evaluated to minimize surface roughness and tool tip temperature as well as to maximize MRR. Optimal process condition has been determined from the analysis of experimental data (Table 3.36).

Initially, aforementioned performance characteristics have been normalized in a range 0 to 1 by using following equations and presented in Table 3.37. For roughness average and tool-tip temperature the Lower-is-Better (LB) criterion and for MRR the Higher-is-Better (HB) criterion has been chosen.

For the Lower- is-Better (LB) criterion:

$$y_{ij} = \frac{x_{ij} - \max x_{ij}}{\min x_{ij} - \max x_{ij}} \tag{3.50}$$

For the Higher- is-Better (HB) criterion:

$$y_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{3.51}$$

Here, x_{ij} is experimental value whereas, $\max x_{ij}$ is the maximum value $\min x_{ij}$ is minimum observed value.

Next, correlations among the responses have been determined (Eq. 3.52) as shown in Table 3.38.

$$R_{jl} = \frac{Cov(x_i(j), x_i(l))}{\sigma_{(x_i)}(j) \times \sigma_{(x_i)}(l)} \tag{3.52}$$

$j = 1, 2, 3, \ldots\ldots\ldots, n; \quad k = 1, 2, 3, \ldots\ldots\ldots\ldots, n$

$Cov(x_i(j), x_i(l))$ is the covariance of sequences $x_i(j)$ and $x_i(l)$, $\sigma_{(x_i)}(j)$ is the standard deviation of sequence $x_i(j)$, $\sigma_{(x_i)}(l)$ is the standard deviation of sequence $x_i(l)$

Furthermore, PCA has been implemented which eliminates the correlation among responses and converts them into uncorrelated quality indices i.e. Principal components. PCA is used to identify the patterns in the correlated data, and express the data in such a form which shows their similarities and dissimilarities (Routara et al., 2010; Datta et al., 2009; Chakravorty et al., 2012). The eigen value and eigen vectors (described in Table 3.39) has been evaluated to further estimate the individual principal components as mentioned in Table 3.40.

$$(R - \lambda_k I_m)V_{ik} \tag{3.53}$$

Here, λ_k eigen values and $\sum_{k=1}^{n} \lambda_k = n, \quad k = 1, 2, \ldots\ldots\ldots\ldots, n;$

$V_{ik} = [a_{k1}, a_{k2}, \ldots\ldots\ldots, a_{kn}]^T$ Eigen vectors corresponding to the Eigen value λ_k

$$PC_{mk} = \sum_{i=1}^{n} x_m(i) . V_{ik} \tag{3.54}$$

Here, PC_{mk} is corresponding Principal Component.

The computed individual principal components have been normalized (Higher-is better) and shown in Table 3.41. These individual principal components have been treated as inputs in Fuzzy Inference System (FIS) (Fig. 3.51). FIS are generally used reduce the uncertainty and vagueness imprecision and/or lack of information regarding the problem. Fuzzy logic is used to define the relationship between system input and desired outputs by utilizing the mathematical theory of inexact reasoning, which interprets human reasoning process to be modelled in linguistic terms (Cox, 1992; Zadeh, 1965; Verma et al., 2011; Abhishek et al., 2013).

Fuzzy logic is based on fuzzification of input data, rule inference and defuzzification to achieve the crisp values. Linguistic variables are used to making the crisp quantity fuzzy during the fuzzification process. These fuzzified data is used by the expert systems to answer reduce the uncertainties and vagueness among responses. There are number of ways such as intuition, inference, rank ordering, angular fuzzy sets, neural networks, genetic algorithms, inductive reasoning, soft partitioning, meta-rules and fuzzy statistics to assign membership values or functions to fuzzy variables. Triangular, trapezoidal, Gaussian and sigmoidal membership functions are commonly used examples of membership functions. In order to determine MPCI, triangular membership function has been assigned to each of the input variables viz. (i) Normalized PC1 (ii) Normalized PC2. (iii) Normalized PC3. The selected membership functions for individual input variables have been: “Low”, “Medium”, and “High”; (Figs. 3.52-3.54); whereas, for MPCI, five membership functions have been assigned: “Very Small”, “Small”, “Medium”, “Large”, and “Very Large” (Fig. 3.55).

A set of rules have been obtained by expert opinion or intuition. The structure of the rules is given as follows: *IF antecedent THEN consequent*

A set of 27 fuzzy rules have been constructed (Fig. 3.56) and demonstrated on Table 3.42. The last stage of fuzzy logic involves defuzzification which can be carried using various methods like max-membership method, centroid method, weighted average method, mean–max membership method, etc. to generate a crisp output. This study has utilized the centroid method to generate the fuzzy crisp output i.e. MPCI (Fig. 3.57). The values (crisp output) have been represented in the Table 3.43.

3.4.4.2 Development of mathematical model (fitness function) and optimization

A mathematical model for aforementioned MPCI has been developed by nonlinear regression analysis using software SYSTAT 7.

$$MPCI = 6.823 \times N^{(-0.242)} \times f^{(0.354)} \times d^{(-0.188)} \qquad R^2 = 98.6\% \tag{3.55}$$

The predicted MPCI has been presented in Table 3.43. In Fig. 3.58 MPCI and predicted MPCI have been compared. Further, relative error (%) has been evaluated to check the adequacy of model as follows:

$$\text{Relative Error (\%)} = \frac{|\text{Actual MPCI value} - \text{Predicted MPCI value}|}{\text{Actual MPCI value}} \tag{3.56}$$

The relative error (%) is 9.237 which shows the effectiveness of proposed model and considered as fitness function for optimization.

To achieve optimum parametric setting for the process responses, evolutionary algorithm such as harmony search algorithm (Chatterjee et al., 2013; Lee and Geem, 2004; Geem et al., 2001; Yang, 2009) and teaching-learning-based optimization algorithm (TLBO) (Rao et al., 2011; Rao and Patel, 2012; Rao and Patel, 2013), have been performed using the objective function (i.e. empirical model of MPCI). The initial parameters for each algorithm have been enlisted in Table 3.44. The MATLAB 12.0 has been used to generate the code for aforesaid algorithm. Flowchart for each algorithm has been illustrated in Fig. 3.59 and Fig. 3.60, respectively. The mathematical model of MPCI has been treated as objective function (which is to be maximized) using aforesaid algorithms. As the code has been developed for minimization of function, therefore the objective function has been made equivalent by multiplying the objective function by (-1). Fig. 3.61 and Fig. 3.62 show the convergence plot generated by HS and TLBO, respectively. The optimal parametric combination for each algorithm has been enlisted in Table 3.45.

From Table 3.45, it has been observed that TLBO appears to be an efficient method for this optimization problem in terms of initial parameters setting. Only 3 parameters are needed to tune to generate the solution. The global optimal solution obtained by aforesaid two algorithms is approximately same. The Signal-to-Noise (S/N) ratio has been computed for MPCI using Higher-is-Better (HB) criterion. It is noted that optimal parametric combination as generated by Taguchi method (Fig. 3.63) appears $N_{220}f_{0.063}d_{0.6.}$and the predicated S/N ratio for parametric combination is greater than computed S/N ratio.

As it is seen from Table 3.45 that the optimal spindle speed appears to be 224.956 RPM through HS algorithm; however, this value cannot be adjusted in the machine/setup. This is because; the machine has the provision of changing factors at some discrete levels (Table 3.34). On the contrary, Taguchi method searches optimal within discrete levels of process parameters. Also, from Table 3.45 it appears that fitness value (MPCI) is maximum (0.8012) for Taguchi method. Therefore, evolutionary algorithms are capable of determining global optimal. If optimal values of process parameters are not available in the machine/set up; parameters need to be adjusted to their next possible (available) values. This kind of problem can easily be avoided by Taguchi method.

3.4.5 Concluding Remarks

In this study, turning of CFRP composites has been carried out by using PVD coated carbide tool. A L_{25} orthogonal array design has been adopted to determine the process parameters combination for conducting the experiments and to obtain performance characteristics with less number of experimental runs. For the optimization of the turning responses, this work proposed hybrid approach for optimization of multi-objective problem using PCA-fuzzy with different meta-heuristic algorithms. The turning process responses such as material removal rate, surface roughness and tool tip temperature are converted to MPCI as a single response using PCA-fuzzy method and developed an empirical equation using non-linear regression analysis between the machining parameters and MPCI. The developed equation is used in meta-heuristics technique such as HS and TLBO to obtain optimum parametric setting.

The major contributions of this work are summarized as below:

1. Principal component analysis has been applied to eliminate response correlation by converting correlated responses into uncorrelated quality indices called individual principal components.
2. Fuzzy Inference System (FIS) has been adopted to convert multi-responses into a single response (objective value), called Multi-Performance Characteristic Index (MPCI).
3. A nonlinear regression model for MPCI has been developed to be treated as fitness function for final optimization through HS algorithm.
4. Effectiveness of the proposed HS and TLBO algorithm has been compared to that of Taguchi’s optimization philosophy.

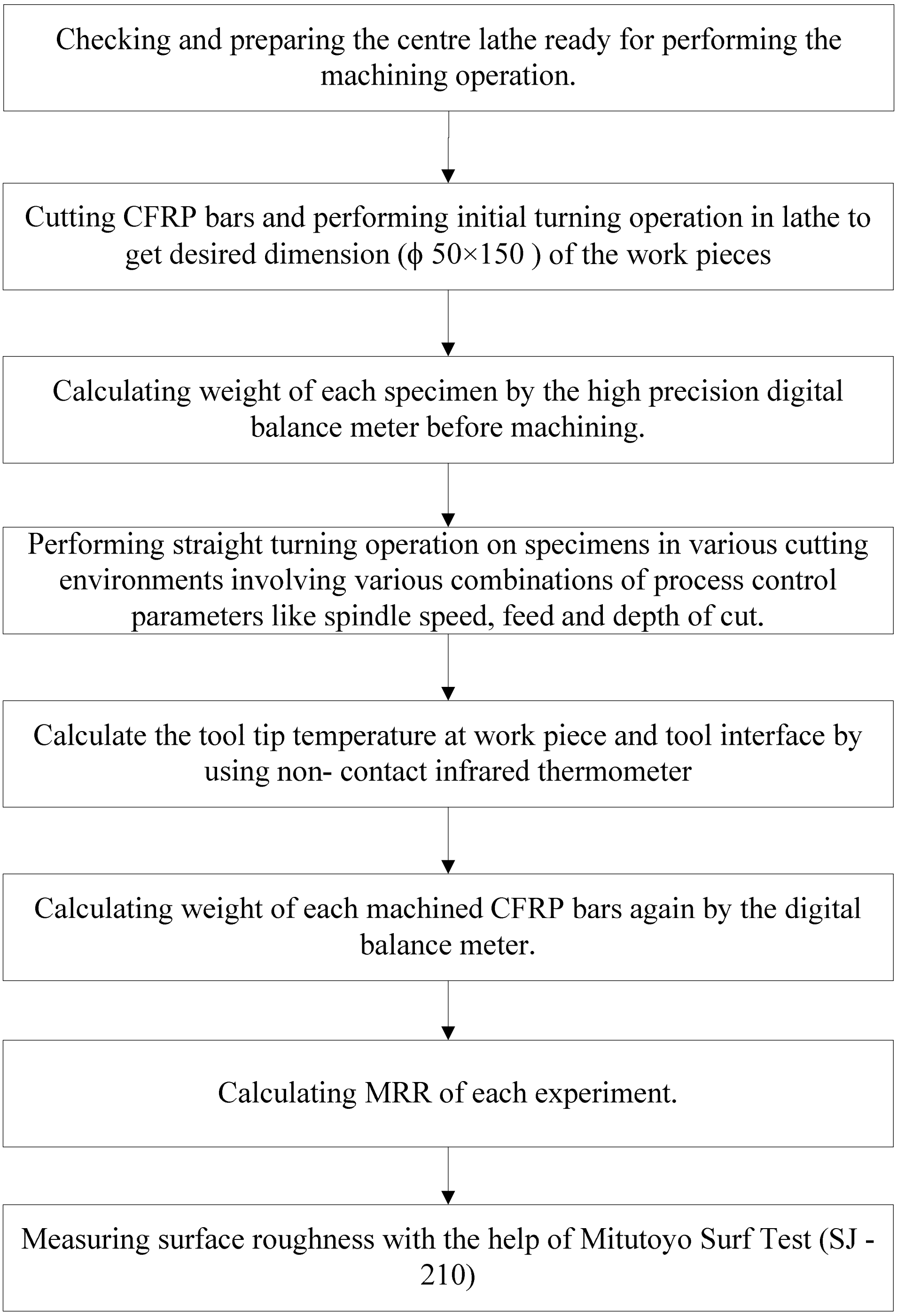


Fig. 3.50: Flow chart of experimental procedure

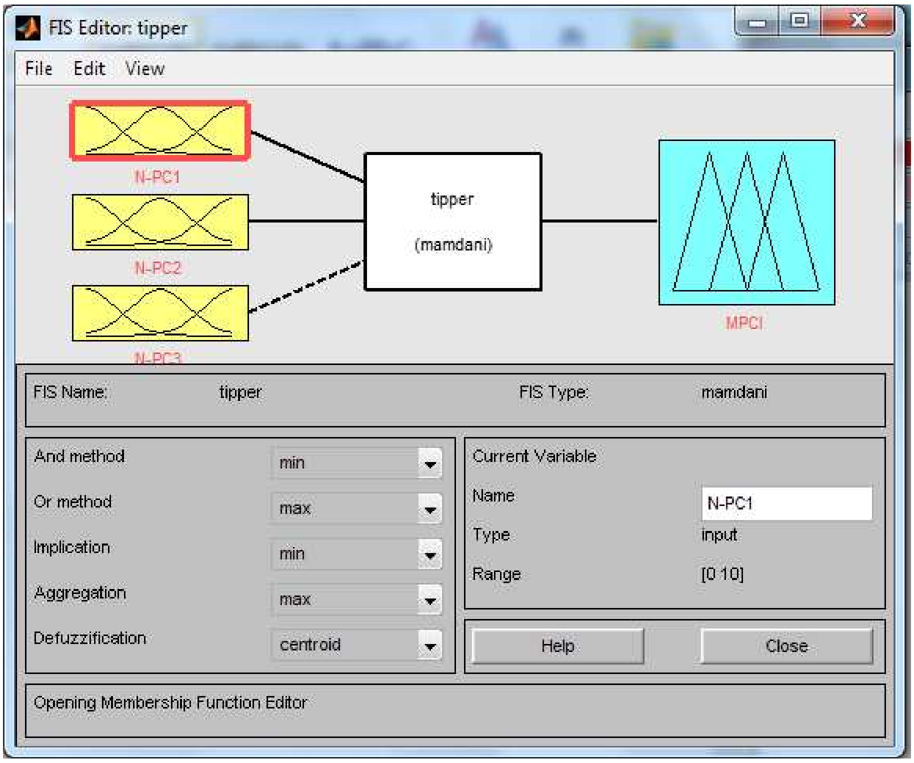


Fig. 3.51: FIS architecture to compute MPCI

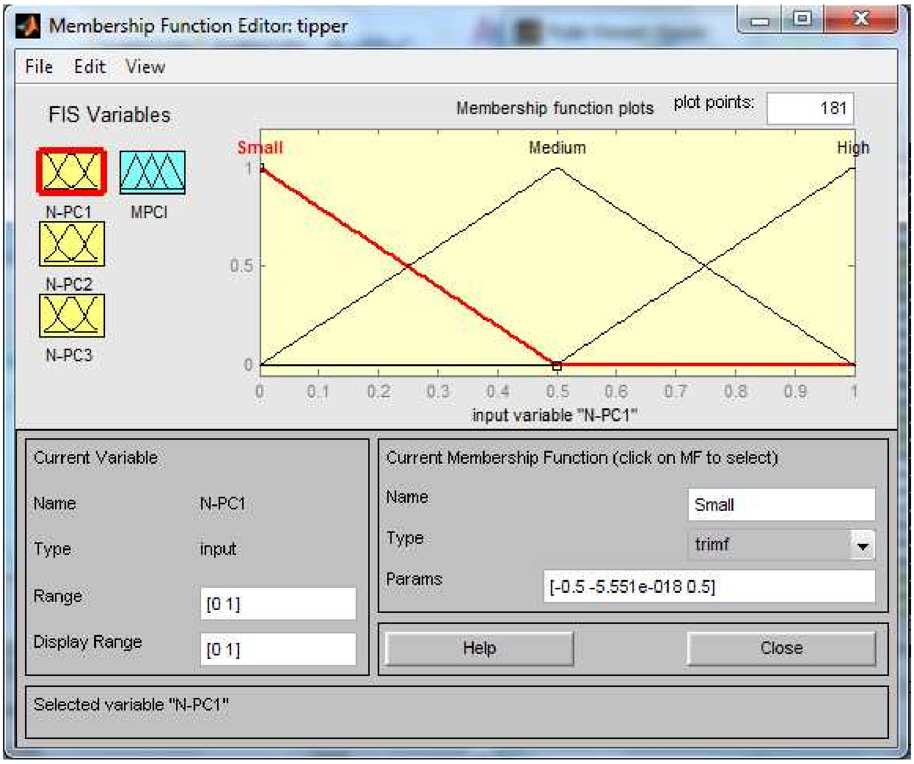


Fig. 3.52: Membership Functions (MFs) for N-PC1

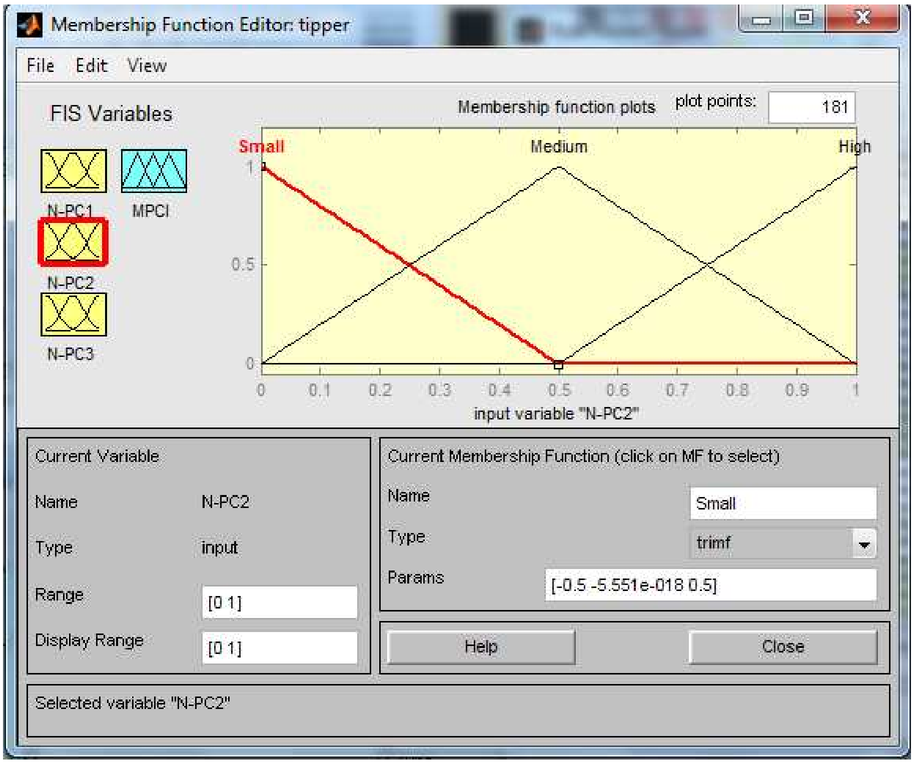


Fig. 3.53: Membership Functions (MFs) for N-PC2

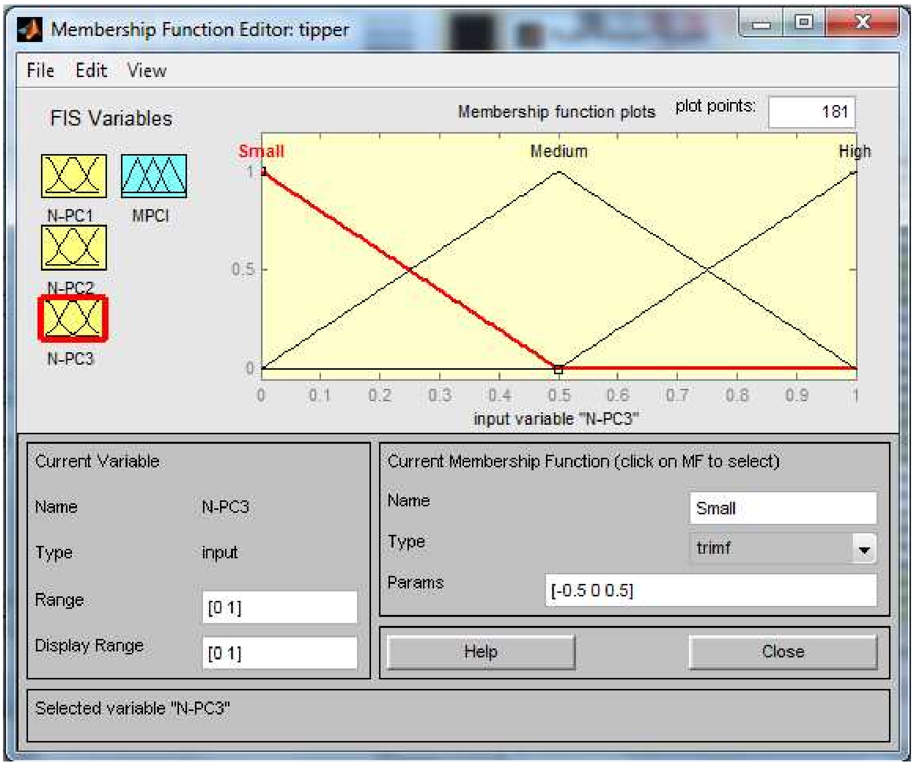


Fig. 3.54: Membership Functions (MFs) for N-PC3

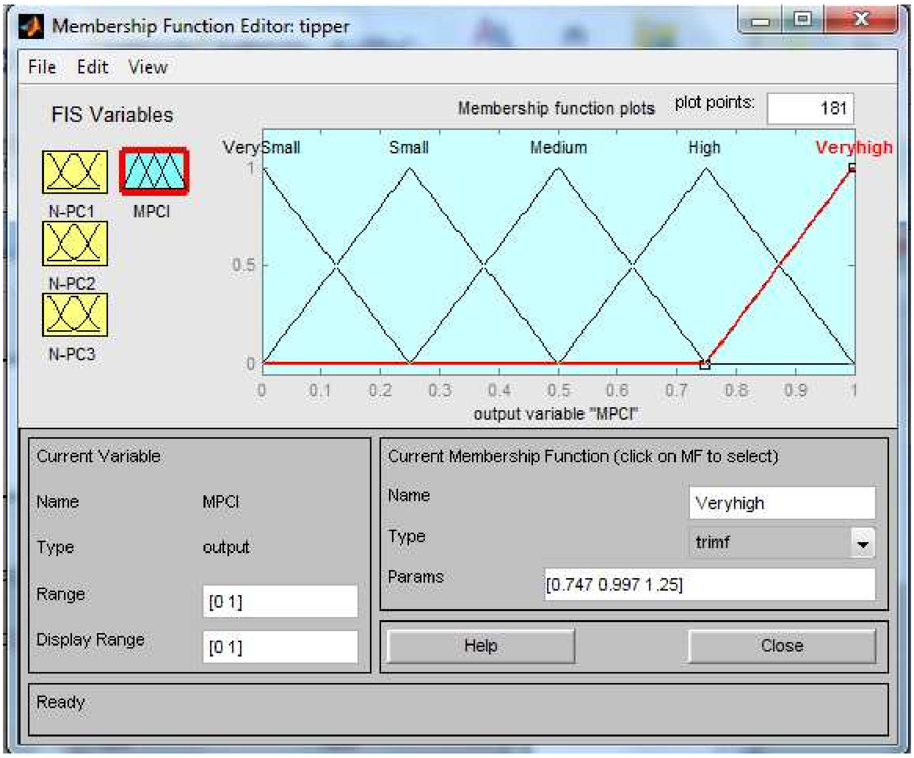


Fig. 3.55: Membership Functions (MFs) for MPCI

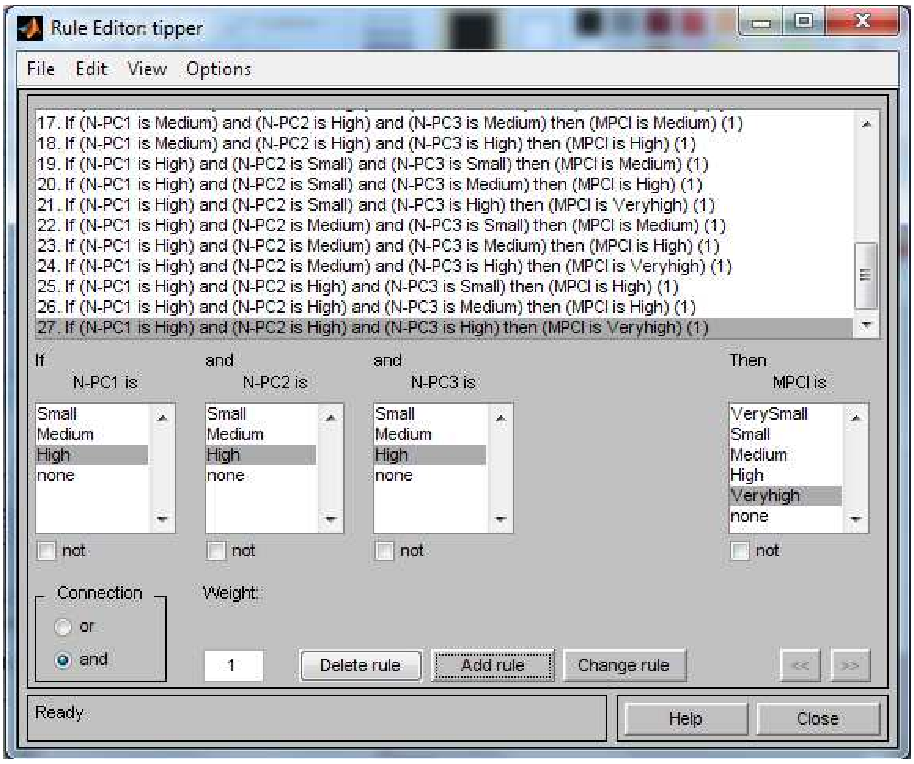


Fig. 3.56: Fuzzy RULE-BASE

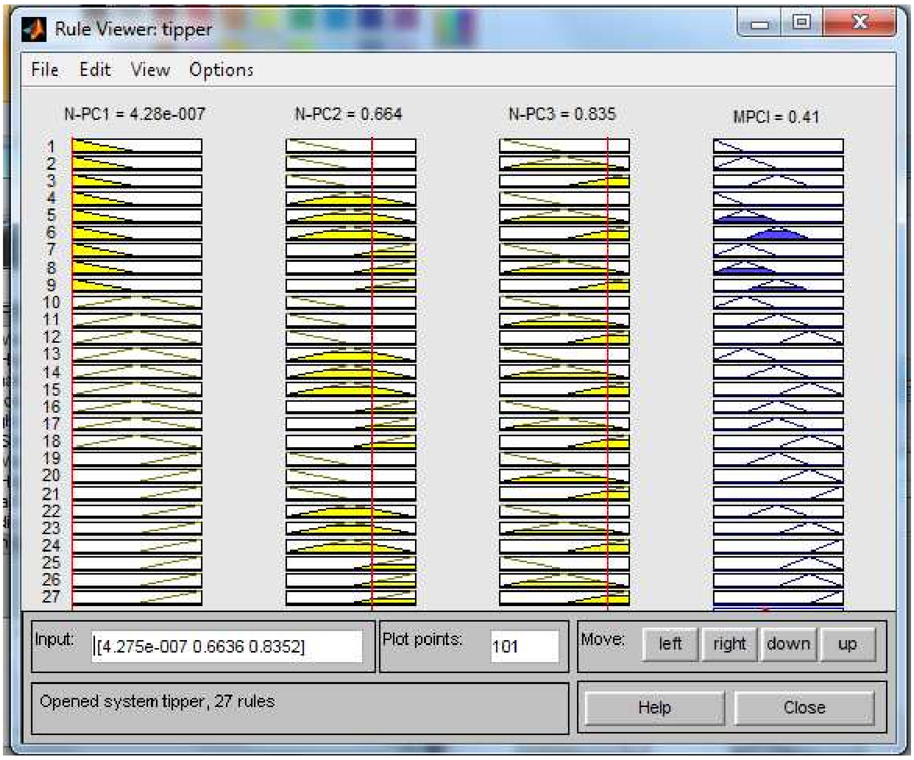


Fig. 3.57: Computation of MPCI based on fuzzy RULE-BASE

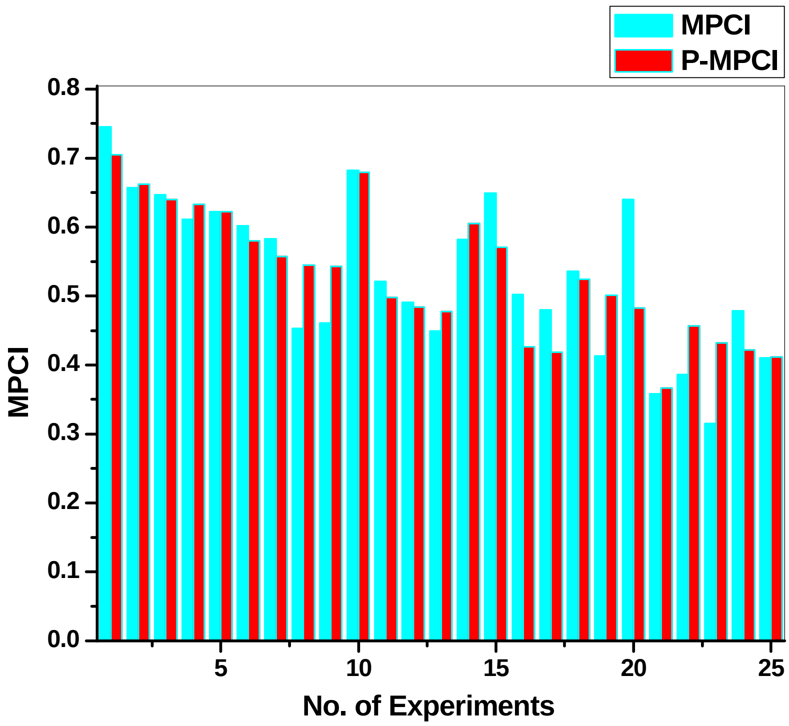


Fig. 3.58: Comparison between MPCI and predicted MPCI

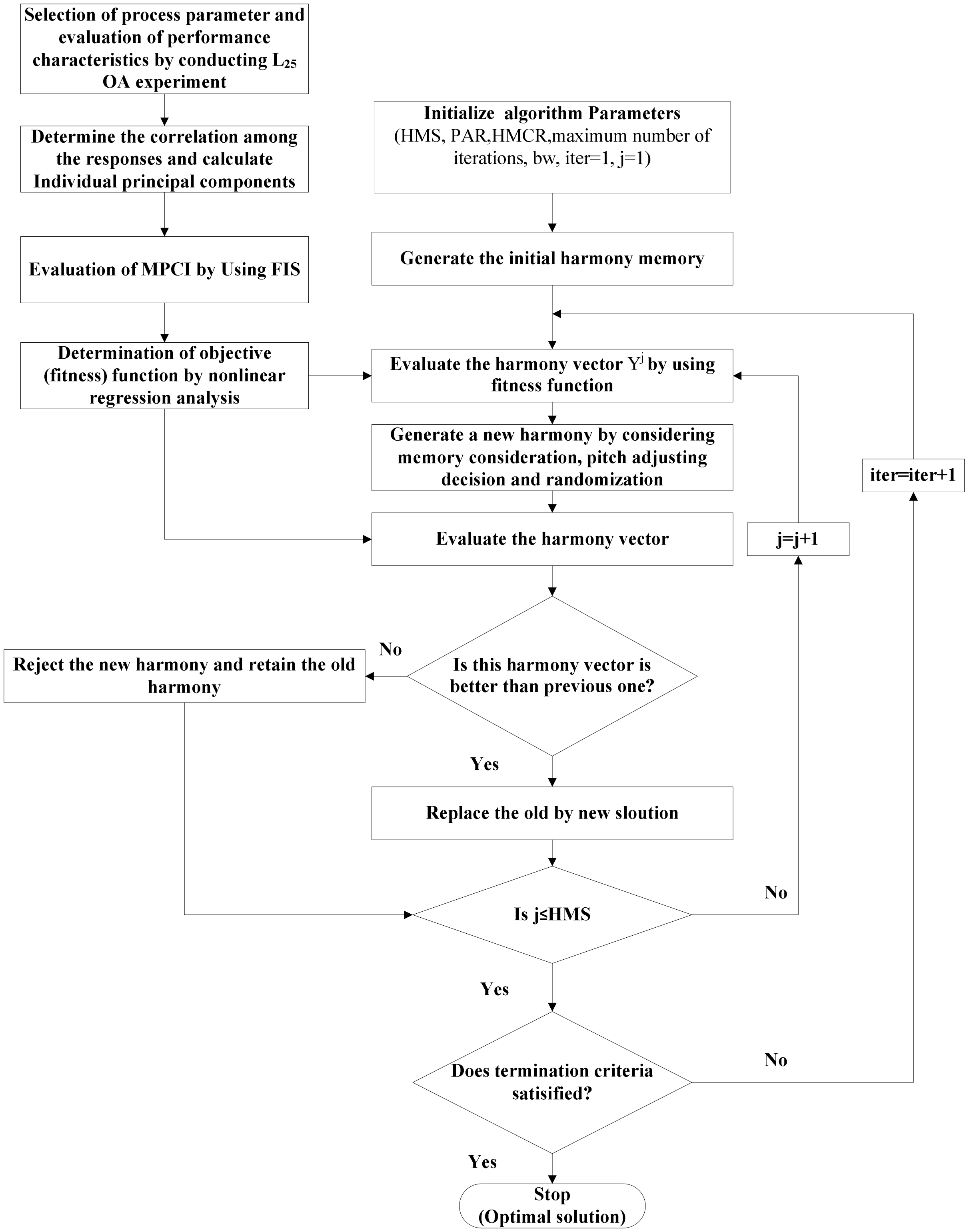


Fig. 3.59: Flow chart for HS algorithm to obtain global optimal solution

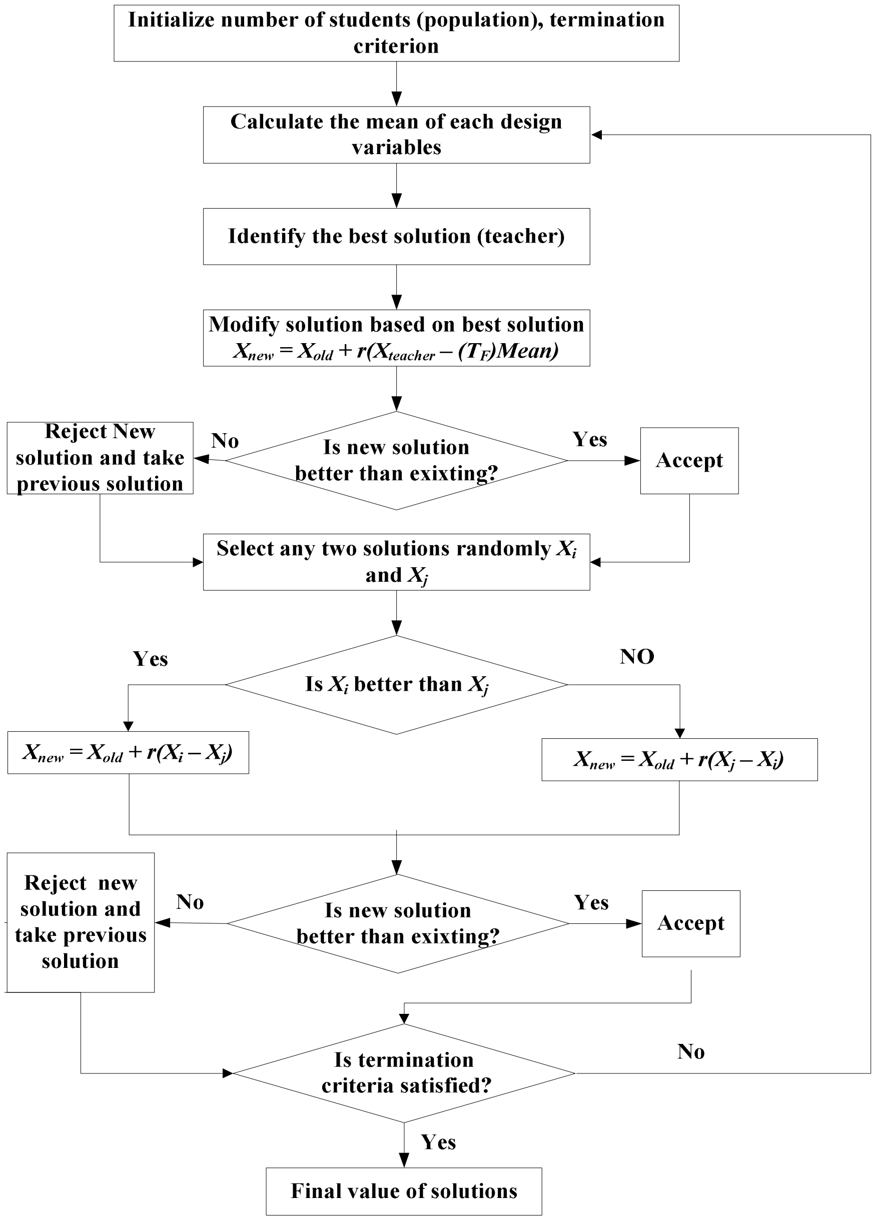


Fig. 3.60: Flow chart for TLBO algorithm to obtain global optimal solution

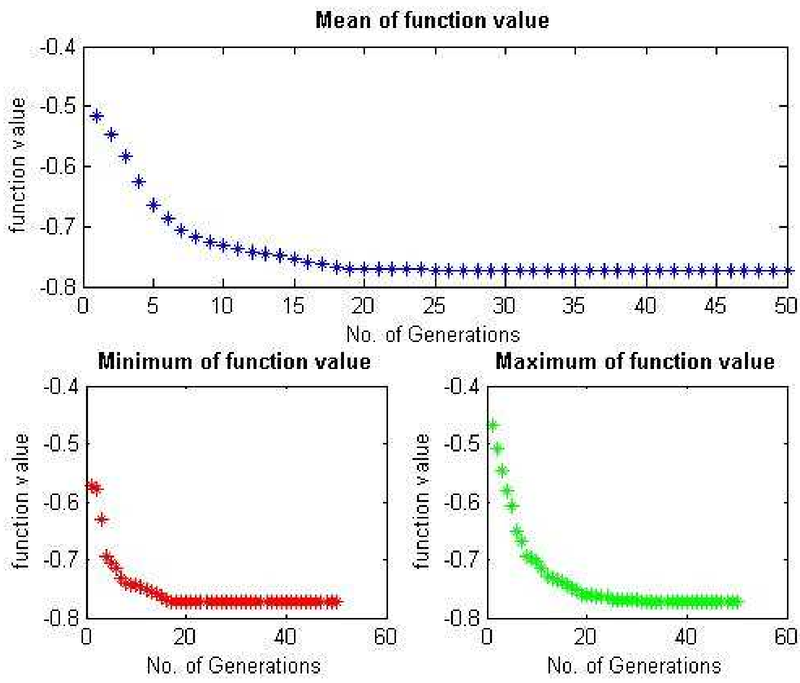


Fig. 3.61: Convergence plot by TLBO

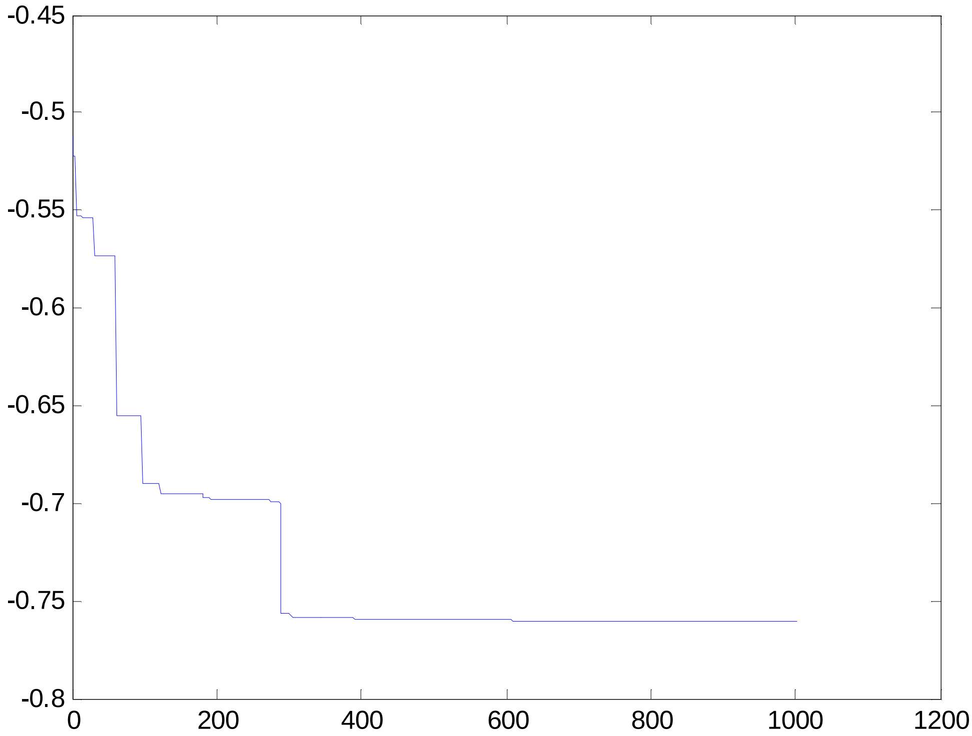


Fig. 3.62: Convergence plot by HS

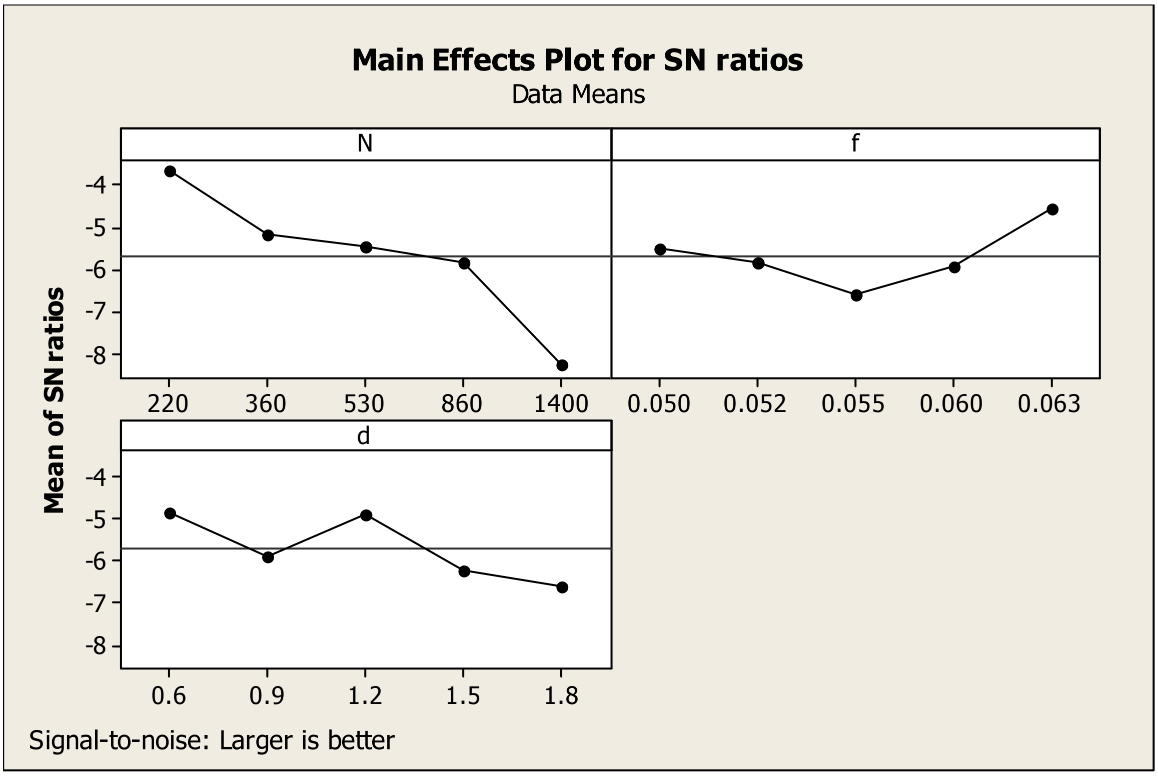


Fig. 3.63: Main effect plot by using Taguchi method

Table 3.34: Domain of experimentation

	Unit	Level 1	Level 2	Level 3	Level 4	Level 5
Spindle Speed	[RPM]	220	360	540	860	1400
Feed rate	[mm/rev]	0.050	0.052	0.055	0.060	0.063
Depth of Cut	[mm]	0.6	0.9	1.2	1.5	1.8

Table 3.35: Design of Experiment (L_{25} Orthogonal Array)

Sl. No.	N [RPM]	f [mm/rev]	D [mm]
1	220	0.050	0.6
2	220	0.052	0.9
3	220	0.055	1.2
4	220	0.060	1.5
5	220	0.063	1.8
6	360	0.050	0.9
7	360	0.052	1.2
8	360	0.055	1.5
9	360	0.060	1.8
10	360	0.063	0.6
11	540	0.050	1.2
12	540	0.052	1.5
13	540	0.055	1.8
14	540	0.060	0.6
15	540	0.063	0.9
16	860	0.050	1.5
17	860	0.052	1.8
18	860	0.055	0.6
19	860	0.060	0.9
20	860	0.063	1.2
21	1400	0.050	1.8
22	1400	0.052	0.6
23	1400	0.055	0.9
24	1400	0.060	1.2
25	1400	0.063	1.5

Table 3.36: Experimental data

Sl. No.	MRR [mm^3/min]	R_a [µm]	Tool-tip Temp. [^{0}C]
1	2546.557	6.181	38.7
2	2919.696	8.794	44.6
3	3266.453	7.834	46.8
4	3666.333	7.997	51.2
5	4173.299	6.615	52.3
6	3739.792	4.328	56
7	4573.219	5.003	58.9
8	3545.957	9.006	61.7
9	3853.163	3.683	63.1
10	4252.563	4.133	51.7
11	4752.723	4.747	60.3
12	5852.163	10.372	62.1

13	5186.429	7.78	63.4
14	4599.68	6.229	57.3
15	5593.115	6.224	59.3
16	5958.888	8.443	64.2
17	6098.509	5.24	69.4
18	6292.675	8.774	62.8
19	6032.427	10.558	65.8
20	6958.888	5.429	66.7
21	6436.094	4.724	77.3
22	6292.675	6.343	72.3
23	6032.427	9.6	75.2
24	7266.453	8.683	70.4
25	7945.32	9.133	74.7

Table 3.37: Normalized experimental data

Sl. No.	N-MRR	N-R_a	N-Tool-tip Temp
1	0.0000	0.6367	1.0000
2	0.0691	0.2566	0.8472
3	0.1333	0.3962	0.7902
4	0.2074	0.3725	0.6762
5	0.3013	0.5735	0.6477
6	0.2210	0.9062	0.5518
7	0.3754	0.8080	0.4767
8	0.1851	0.2257	0.4041
9	0.2420	1.0000	0.3679
10	0.3160	0.9345	0.6632
11	0.4086	0.8452	0.4404
12	0.6123	0.0271	0.3938
13	0.4890	0.4041	0.3601
14	0.3803	0.6297	0.5181
15	0.5643	0.6304	0.4663
16	0.6321	0.3076	0.3394
17	0.6579	0.7735	0.2047
18	0.6939	0.2595	0.3756
19	0.6457	0.0000	0.2979
20	0.8173	0.7460	0.2746
21	0.7204	0.8486	0.0000
22	0.6939	0.6131	0.1295
23	0.6457	0.1393	0.0544
24	0.8743	0.2727	0.1788
25	1.0000	0.2073	0.0674

N~Normalized

Table 3.38: Check for correlation

Correlation between	Pearson’s Correlation Coefficient
MRR and Ra	-0.245
MRR and Tool tip temperature	0.861
Ra and Tool tip temperature	0.122

Table 3.39: Results of PCA

	PC1	PC2	PC3
Eigen value	1.9335	0.9365	0.1299
Eigen vector	$\begin{vmatrix} -0.690 \\ 0.269 \\ 0.672 \end{vmatrix}$	$\begin{vmatrix} -0.117 \\ -0.958 \\ 0.263 \end{vmatrix}$	$\begin{vmatrix} 0.714 \\ 0.103 \\ 0.692 \end{vmatrix}$
AP	0.645	0.312	0.043
CAP	0.645	0.957	1.000

Table 3.40: Computed major Principal Components (PCs)

Sl. No.	PC1	PC2	PC3
1	0.8433	-0.3469	0.7576
2	0.5906	-0.0311	0.6620
3	0.5456	-0.1874	0.6828
4	0.4115	-0.2033	0.6544
5	0.3816	-0.4144	0.7224
6	0.4621	-0.7489	0.6330
7	0.2787	-0.6926	0.6811
8	0.2046	-0.1316	0.4351
9	0.3492	-0.8896	0.5304
10	0.4790	-0.7578	0.7808
11	0.2414	-0.7417	0.6836
12	-0.1506	0.0060	0.7125
13	0.0133	-0.3496	0.6399
14	0.2552	-0.5115	0.6949
15	0.0936	-0.5473	0.7905
16	-0.1253	-0.2794	0.7178
17	-0.1084	-0.7642	0.6911
18	-0.1565	-0.2310	0.7821
19	-0.2453	0.0028	0.6672
20	-0.1787	-0.7381	0.8504
21	-0.2688	-0.8972	0.6018
22	-0.2268	-0.6345	0.6482
23	-0.3715	-0.1947	0.5130
24	-0.4098	-0.3166	0.7760
25	-0.5890	-0.2979	0.7820

Table 3.41: Normalized PCs and aggregated MPCI as obtained from FIS

Sl. No.	N-PC1	N-PC2	N-PC3	MPCI
1	1.0000	0.6093	0.7765	0.745
2	0.8236	0.9589	0.5464	0.657
3	0.7921	0.7859	0.5964	0.647
4	0.6985	0.7683	0.5280	0.611
5	0.6777	0.5346	0.6918	0.622
6	0.7339	0.1643	0.4765	0.602
7	0.6058	0.2265	0.5924	0.583
8	0.5541	0.8476	0.0000	0.453

9	0.6551	0.0085	0.2294	0.461
10	0.7457	0.1543	0.8324	0.682
11	0.5798	0.1722	0.5983	0.521
12	0.3061	1.0000	0.6678	0.491
13	0.4205	0.6063	0.4932	0.449
14	0.5894	0.4271	0.6256	0.582
15	0.4766	0.3874	0.8558	0.649
16	0.3237	0.6840	0.6808	0.502
17	0.3356	0.1473	0.6163	0.480
18	0.3019	0.7376	0.8355	0.536
19	0.2400	0.9965	0.5588	0.413
20	0.2865	0.1762	1.0000	0.640
21	0.2235	0.0000	0.4014	0.358
22	0.2529	0.2909	0.5132	0.386
23	0.1519	0.7778	0.1876	0.315
24	0.1251	0.6429	0.8208	0.478
25	0.0000	0.6636	0.8352	0.410

Table 3.42: Fuzzy rule matrix

Sl. No	IF			THEN
	N-PC1	N-PC2	N-PC3	MPCI
1	Small	Small	Small	Very small
2	Small	Small	Medium	Small
3	Small	Small	High	Medium
4	Small	Medium	Small	Very small
5	Small	Medium	Medium	Small
6	Small	Medium	High	Medium
7	Small	High	Small	Small
8	Small	High	Medium	Small
9	Small	High	High	Medium
10	Medium	Small	Small	Small
11	Medium	Small	Medium	Medium
12	Medium	Small	High	High
13	Medium	Medium	Small	Small
14	Medium	Medium	Medium	Medium
15	Medium	Medium	High	High
16	Medium	High	Small	Medium
17	Medium	High	Medium	Medium
18	Medium	High	High	High
19	High	Small	Small	Medium
20	High	Small	Medium	High
21	High	Small	High	Very high
22	High	Medium	Small	Medium
23	High	Medium	Medium	High
24	High	Medium	High	Very high
25	High	High	Small	High
26	High	High	Medium	High
27	High	High	High	Very high

Table 3.43: MPCI as obtained from FIS and predicted MPCI from the non-linear regression model

Sl. No.	MPCI	P-MPCI
1	0.745	0.705102
2	0.657	0.662486
3	0.647	0.640194
4	0.611	0.633096
5	0.622	0.622421
6	0.602	0.579947
7	0.583	0.557095
8	0.453	0.544921
9	0.461	0.543031
10	0.682	0.679242
11	0.521	0.498064
12	0.491	0.48428
13	0.449	0.477346
14	0.582	0.605214
15	0.649	0.570565
16	0.502	0.426734
17	0.480	0.41812
18	0.536	0.524352
19	0.413	0.501066
20	0.640	0.482956
21	0.358	0.366485
22	0.386	0.456862
23	0.315	0.43182
24	0.478	0.421883
25	0.410	0.411599

Table 3.44: Settings of Initial parameters for optimization algorithms

Harmony Search	TLBO
Maximum No. of iterations= 1000 Harmony memory size= 6 harmony consideration rate (HMCR)= 0.9 Minimum pitch adjusting rate (PARmin)= 0.4 Maximum pitch adjusting rate (PARmax)= 0.9 Minimum bandwidth (bwmin)= 0.0001 Maximum bandwidth (bwmax)=1	Population size= 10, Maximum Number of generation= 50 Teaching factor =2

Table 3.45: Optimal machining condition by different methodologies

Material	Algorithm/methodology	Optimal Parametric Combination			Fitness value (MPCI)
		Spindle speed [RPM]	Feed rate [mm/rev]	Depth of cut [mm]	
CFRP	HS	224.956	0.06300	0.6000	0.7602
	TLBO	220	0.06300	0.6000	0.7727
	Taguchi Method	220	0.06300	0.6000	0.8012

CHAPTER 4

CONCLUSIONS, THESIS CONTRIBUTIONS AND SUGGESTIONS FOR FUTURE WORK

The contributions of the present dissertation have been summarized below.

- In case of negligible response correlation, Deng's similarity method combined with Taguchi philosophy can be very effective for solving multi-response optimization problems in the context of machining CFRP composites.
- Evolutionary algorithms like HS, TLBO, ICA etc. can be well articulated to suit optimization problems in machining of CFRP composites. If the problem is involved with multi-performance features; Fuzzy Inference System (FIS) can be efficiently explored to aggregate multiple performance features into a single index called Multi-Performance Characteristic Index (MPCI). Using nonlinear regression, an equivalent fitness function can be derived so as to represent MPCI as a function of input process parameters. The fitness function of MPCI can be optimized by an optimization algorithm in order to obtain the global optima.
- However, the global optima as obtained by aforesaid fuzzy based evolutionary algorithms may not be feasible in practice due to non-availability of the optimal values of process parameters in the machine/setup. This is because, in most of the machines/setups, provision is there to adjust the process parameters at some discrete levels. On the contrary, Taguchi method searches near-optimal solution within discrete domain of process parameters. Hence, application potential of PCA-Fuzzy-Taguchi integrated optimization approach has been recommended here for correlated multi-response optimization in machining of CFRP composites.

Suggestions of future work have been pointed out below.

- Interaction effect of process parameters can be investigated in detail.
- Effect of variation of cutting tool material/tool geometry on machining performance can be examined.
- Aspects of tool wear can be investigated in relation to machining of CFRP composites.
- Mechanics of chip formation and the critical influence of composite architecture on chip formation mode, cutting force and surface quality can be studied.
- The issues of health and safety in machining of FRP composites can be attempted.

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List of Publications

Journal Publications

Kumar Abhishek, Saurav Datta, Siba Sankar Mahapatra, 2015, *Optimization of Thrust, Torque, Entry and Exit Delamination Factor during Drilling of CFRP Composites*, **International Journal of Advanced Manufacturing Technology**, 76(1): 401-416, Springer-Verlag London Limited.

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Kumar Abhishek, V. Rakesh Kumar, Saurav Datta, Siba Sankar Mahapatra, *Parametric Appraisal and Optimization in Machining of CFRP Composites by using TLBO (Teaching-Learning Based Optimization)*, **Journal of Intelligent Manufacturing**, Springer-Verlag London Limited. **(Published Online)** DOI 10.1007/s10845-015-1050-8

Kumar Abhishek, Saurav Datta, Siba Sankar Mahapatra, *Multi-Objective Optimization during Drilling of CFRP Composites: A PCA-Fuzzy Taguchi Integrated Approach*, **International Journal of Industrial and Systems Engineering**, Inderscience Publishers, Switzerland. **(Accepted)**

Kumar Abhishek, Saurav Datta, Siba Sankar Mahapatra, 2016, *Multi-objective Optimization in Drilling of CFRP (Polyester) Composites: Application of a Fuzzy Embedded Harmony Search (HS) Algorithm*, **Measurement**, Vol. 77, pp. 222-239, Elsevier Science.

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Kumar Abhishek, Saurav Datta, Siba Sankar Mahapatra, *PCA-Fuzzy based Taguchi Approach for Parametric optimization in Machining of CFRP Composites*, **International Conference on Computational Intelligence and Advanced Manufacturing Research (ICCIAMR-2013)**, held during 5-6 April 2013, organized by Department of Mechanical Engineering, VELS University, Chennai 600117, India.

Kumar Abhishek, Saurav Datta, Siba Sankar Mahapatra, *Desirability Function, Principal Component Analysis and Grey integrated Taguchi Method for Parametric Optimization in Machining of CFRP composites*, **International Conference on Advances in Mechanical Engineering (ICAME-2013**), held during 29-31 May 2013, organized by Department of Mechanical Engineering, College of Engineering Pune, Shivaji Nagar, Pune 411 005, India.

Kumar Abhishek, Saurav Datta, Siba Sankar Mahapatra, *Response Surface Modeling on Machining of CFRP Composites: Effect of Process Variables on Surface Roughness, MRR and Tool-Tip temp*, **International Conference on Advances in Mechanical**, **Automobile and Aerospace Engineering (AMAAE-2013)**, organized by *Krishi Sanskriti*, held during 21-22 September 2013, at Jawaharlal Nehru University, New Delhi 110067, India.

Kumar Abhishek, Saurav Datta, Suman Chatterjee, Siba Sankar Mahapatra, *Parametric Optimization in Turning of CFRP (epoxy) Composites: A Case Experimental Research with Exploration of HS Algorithm*, **6th International Conference on Mechanical and Electrical Technology (ICMET 2014)**, held during 17-18 July 2014 in Bangkok, Thailand.

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